Doctoral Dissertation

On Variability and Heterogeneity of Day- to- Day Travel

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Graduate School of Engineering
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Abstract

This study is concerned with how an individual's daily travel pattern vary from-day-to-day and how people different in term of daily travel pattern. Day-to-day variation in travel pattern occurs because people do not have the same needs and desires every day. There are trips that are highly routine and made regularly on a daily basis independent of other trips and activity engagements, and there are activities that are engaged in with longer intervals, such as weekly shopping. Also, there are activities that do not have particular cycles for engagement and take place in haphazard manners, such as a trip to a furniture store. Therefore, day-to-day variation in individuals needs as well as different needs across people have put the individual daily travel pattern into a dynamic process. Knowing the nature of this variation, in spectrum from perfectly repetitions to purely random, would lead to not only a better understanding of daily travel behavior, but also to better development and evaluation of planning measures.

Understanding variability in travel patterns is one of the central issues in modeling travel behavior and has been discussed intensively (Hanson and Huff, 1982; Pas, 1988; Kitamura, 1988; Keuleers et al. , 2001; Schlich and Axhausen, 2003 and Schlich et al., 2003). As Jones and Clarke (1988) note, as the emphasis of transportation planning has shifted from capacity expansion to the formulation of transportation policies aimed at effectively managing travel demand, some of the issues facing planners cannot be addressed by one-day data while ignoring variations in behavior over time. Hanson and Huff (1986) argue that without information on day-to-day variability, it is impossible to determine exactly how much of the interpersonal variability in travel pattern is genuine, and how much is the artifact of intra-person, day-to-day variability.

The findings of previous research motivate a need more study the characteristics of day-to-day variations in individual's daily travel patterns and particularly, the stochastic

characteristics of activity engagements and trip making; heterogeneity in travel pattern variations, i.e., differences across individuals in variation characteristics of daily travel pattern. In addition, it is important to note that most of past studies have narrowly focused on specific aspect of travel, e.g., trip rate a particular trip purpose (e.g., shopping, working) or visits at a frequented location. It has been rare that the variability in daily travel patterns in their entirely is examined over a long span of time. Moreover, only limited knowledge exists on how different individuals exhibit different patterns of day-to-day variability.

This study has develops the framework for the analysis of multi-day travel patterns. The focus has been on the recurrence of daily travel patterns as a whole over a long span of time, and how it varies from individual to individual. The objective of day-to-day variability analysis is to examine the nature how the daily travel as whole caries, how repetitious is travel and to quantify the patterns of day-to day variation for each individual. Then objective of heterogeneity analysis is to examine the distribution of the parameter values across individual to test how patterns of-day-to-day variation is different across individual, how people different in term of multi-day travel pattern.

It is clear that multi-day travel data are a prerequisite for the analysis of the variability in travel behavior over time, as only such data would be able to offer information on the stochastic nature of daily travel patterns. In this study, individuals' multi-day travel patterns are analyzed using the Mobi*drive* data set (Axhausen et. al., 2002) that contains travel records obtained from a continuous six-week travel diary survey. The survey was carried out with the aim of obtaining a more detailed picture of mobility patterns and to develop methodological approaches to capture behavioral variability.

In an attempt to treat daily travel as a whole, yet in a manageable manner, principal component analysis (PCA) and *k*-mean cluster analysis are applied to the six-week diary data to identify a small number of travel pattern classes with strong internal similarities in travel pattern characteristics. Then, the recurrence structure of daily travel patterns over a course of days is analyzed by Markov chain models. In addition, a two-state Markov chain model is applied to examine the recurrence of daily patterns. Through these analyses, this study attempts to identify salient characteristics multi-day travel with focus on the recurrence structures of daily patterns.

The study offers new empirical findings on the variation of travel patterns from day to day and interconnection between different travel patterns. For example, transitions from a daily pattern to itself are often frequent, particularly among non-workers, and some daily patterns tend to be persistent with successive engagement over a large number of days.

In order to reveal the heterogeneity in multi-day travel pattern, the pattern-to-pattern transition probabilities and expected sojourn durations in travel pattern both estimated for each individual. Unobserved heterogeneity across individual is investigated. The study has revealed that individuals, either worker or non-workers, are heterogeneous in terms of multi-day travel behavior; their pattern-to-pattern transition probabilities vary substantially across individuals. Empirical results also indicate that, for example, having a driver's license tends to contribute to a higher level of day-to-day variability in travel patterns. It is also shown that variability in daily travel is highly dependent on the individual's residence location; an individual living in central area is more likely to regularly pursue travel patterns with shopping and leisure activities.

This study is one of the early attempts of applying a stochastic-process framework to the analysis of multi-day travel behavior. A rich set of research subjects remains to be explored in the future. For example, unexplored subjects include travel patterns on weekend days, how they are related to those on weekdays, and how the weekly cycle affects the recurrence of travel patterns. In closing, I would like to emphasize that the empirical results from the study have important implications for transportation policy analysis and travel modeling.

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CHAPTER 1
Introduction

1.1 Research Background

Individual's daily activity and travel pattern varies from day to day, from week to week, or from season to season, in part because the individual and his household have needs and desires that vary over time. Knowing the nature of this variation, in spectrum from perfectly repetitions to purely random, would lead to not only a better understanding of daily travel behavior, but also to better development and evaluation of planning measures. As Jones and Clarke (1988) note, as the emphasis of transportation planning has shifted from capacity expansion to the formulation of transportation policies aimed at effectively managing travel demand, some of the issues facing planners cannot be addressed by one-day data while ignoring variations in behavior over time.

For example, suppose one wishes to know exactly who would be directly affected by a region-wide road pricing scheme where a congestion charge is imposed during the morning peak period. To address this question, one must determine who would continue to travel during the morning peak period, change departure time, change mode, quit traveling altogether, etc. This, however, varies from day to day because, to begin with, people do not always travel during the peak period, or they may not always be able to change departure time or travel mode to avoid congestion pricing, etc. Thus, to assess the impact of the pricing scheme, one must know the nature of variation in people's daily travel. Likewise, to know by whom and how a community-based special-purpose transit service is used and how its cost should be borne, one will have to see how each community member uses, or does not use, the service over a span of time. As one can easily imagine by contemplating on how his/her morning travel could be modified in response to congestion pricing, a trip is an integral part of daily activity and travel. In this sense, one would wish to know how daily travel as a whole varies and how respective trips contained in daily patterns vary from day to day. Given this, a question that arises is how to depict an individual's daily travel and how to characterize its variation from day to day.

However, in spite of the fact that theoretical discussions recognize the day-to-day variability inherent in travel behavior, most of the recent urban travel demand analyses are still based on one-day data, which containing records of trips made by household members on a given survey day. The basic reason of this approach is that if the behavior reported is for a randomly chosen day (out of some longer time period) then an unbiased sample of behavior (over that time period) is obtained. Further, such one-day travel behavior surveys are commonly conducted in such a way that travel behavior information is obtained for the different weekdays. Since the sampling methods employed generally avoid the situation where the characteristics of households or individuals are correlated with the days of the week, this approach leads to unbiased samples of travel behavior on an average weekday and to unbiased estimates of the parameters in the models estimated with such data (Pas and Sundar, 1994). One day data, however not able to reveal the dynamic properties of day-to-day and week-to-week changes in travel pattern. Statistical analysis of one day data would not provide a correct depiction of behavior if it is history dependent. One-day data also do not yield how many people are likely to maintain the same travel and or/ activity patterns over time, how often do people "move" from one pattern to another.

Since individual daily travel pattern is a dynamic phenomenon with both complex short and long-term variability, the use of multi-day data in travel behavior analysis is clearly important. The advantages in using multi-day data are:

- Multi-day data can provide valuable data that allow the analysis, understanding and modeling of variation in travel pattern over time (Zimowski et al., 1997)
- Multi-day travel data have come to attract the attention of transport researchers who wish to evaluate non-conventional transport policies under diversified travel demands (Jones et al., 1990).
- Longitudinal observation of repeated travel decisions (e.g., work trip mode choice over a week) will make it possible to examine the stochastic nature of the choice. (Kitamura, 1988).

- Variation in daily travel pattern influenced by observable factors, and unobservable factors as well. Capturing these factors in travel behavior, however, could not be done without longitudinal data.

Some of statistical benefits of using multi-day data are evident in the study by Goodwin (1978) into the pattern of car use in Oxford. His finding is the variation in intensively with which car are used is reduced as more days' are included in the analysis. The coefficient of variation of "minutes car are in use" steadily reduces from 1.1 for one day to 0.7 for five-weekdays data-with about half reduction occurring at day two.

Hanson and Huff (1990) when we looked at recurrence of certain behaviors within the individual's longitudinal record, we found that many of them-however defined –occurred at essentially random intervals. How to compare behavior from time period to time period remains problematic, however, when so much of the short term temporal variability in travel is essentially random. In the context of variability in behavior over a series of consecutive days, important distinction is drawn between intrapersonal and interpersonal variability. (Koppelman and Pas, 1984).

Herz (1983) for example, describes a study in which he used cluster analysis to aggregate 271 person type categories and found that he could account for 60% to 90% of the variability in behavior between the original 271 units with five to seven socio-demographic clusters. However, in term of total variability between all 65000 individuals in the sample, he found only between 3% to30% of this could be explained by these clusters-and that the level of statistical explanation was hardly improved by reverting to original 271 categories. He concludes that multi-day data are needed to produce more realistic taxonomies.

The findings of previous research motivate a need more study the characteristics of day-to-day variations in individual's daily travel patterns and particularly, the stochastic characteristics of activity engagements and trip making; heterogeneity in travel pattern variations, i.e., differences across individuals in variation characteristics of daily travel pattern.

In addition, it is important to note that most of past studies have narrowly focused on specific aspect of travel, e.g., trip rate a particular trip purpose (e.g., shopping, working) or visits at a frequented location. It has been rare that the variability in daily travel patterns in their entirely is examined over a long span of time. Moreover, only limited knowledge exists on how different individuals exhibit different patterns of day-to-day variability.

This study intends to provide to questions such as;

- (Day-to-day variability in daily travel pattern): How daily travel as a whole varies? How repetitious is travel? How the day-to-day variations are quantified in the model?
- (Heterogeneity in travel pattern variation) – How patterns of day-to day variation are different across individuals? How people different in the term of multi-day travel pattern? How people often change their daily travel pattern? Can we explain heterogeneity across individuals?

1.2 Research Objectives

The objectives of this study are:

1. To develop the framework for analysis of multi-day travel pattern, the focus is on day-to-day variations in the individual's daily travel patterns.
2. To analyze the recurrence structure of daily travel patterns over a course of days
3. To quantify patterns of day-to-day variation for each individual.
4. Then to examine the distribution of the parameter values across individuals and how patterns of day-to-day variation are different across individuals.
5. To test the history dependence in transition from daily pattern to pattern and investigate the unobserved heterogeneity across individual.

This study presents a framework for the analysis of multi-day travel behavior and thereby offers new empirical findings on the variation of travel patterns from day to day. Moreover, this study first calibrates model parameters to quantify patterns of day-to-day variation for each individual.

Analyzing the characteristics of multi-day travel behavior as a stochastic process, then, examining recurrence structure of daily travel patterns over a course of days, testing unexplained differences in transition probabilities across individuals are unique and important contribution of this study as well.

In this study, individuals' multi-day travel patterns are analyzed using the Mobidrive data set (Axhausen et. al., 2002) that contains travel records obtained from a continuous six-week travel diary survey. The survey was carried out with the aim of obtaining a more detailed picture of mobility patterns and to develop methodological approaches to capture behavioral variability. After a pre-test of the survey instruments with a smaller sample in Spring 1999, a total of 317 persons over six years of age from 139 households participated in the main phase of the survey.

1.3 Outline of Dissertation

The outline of the dissertation is as follows. **Chapter 1** explains the background, the objectives of the study.

Past studies on day-to day variation in travel and multi-day travel pattern, the frameworks and methodologies for the analysis of variability of travel patterns from day to day are presented in **Chapter 2.** The *hypotheses* of this study are presented in last part of this chapter.

Chapter 3 describes the used data sets of this study, i.e. *Mobidrive* six-week continuous travel diary data.

Chapters 4 identify a small number of travel pattern classes which are interpretable and reflect the many aspects of daily travel patterns. This is done by PCA and k means cluster analysis.

Then, the multi-day travel behavior is analyzed by applying stochastic-process approach in **Chapter 5**. Present study offers two kinds of Markov chain models:

- The recurrence structure of travel pattern classes over a course of days is analyzed by applying discrete-state Markov chain models first. As a reasonably large number of day-to-day transitions are observed for each sample individual in the data set, transition probabilities are estimated for each individual, and their variations across individuals are examined. Mean stopping time (the expected number of days until a travel pattern class will be observed again after it is first observed). The power of transition matrix of daily travel pattern is investigated then by its limiting distribution.
- The occurrence probability of daily travel pattern and its sojourn duration are estimated by two-state Markov chain model. The estimated mean sojourn duration in each pattern is examined then by regression model.

Chapter 6 provides the answer on question *Who has a homogenous travel pattern over days and who does not?*.

A mixed logit model applied in **Chapter 7** to account the unexplained differences in transition probabilities across individuals and examine the characteristics of history dependence in the transition between daily travel patterns.

Chapter 8 closes the dissertation with conclusion.

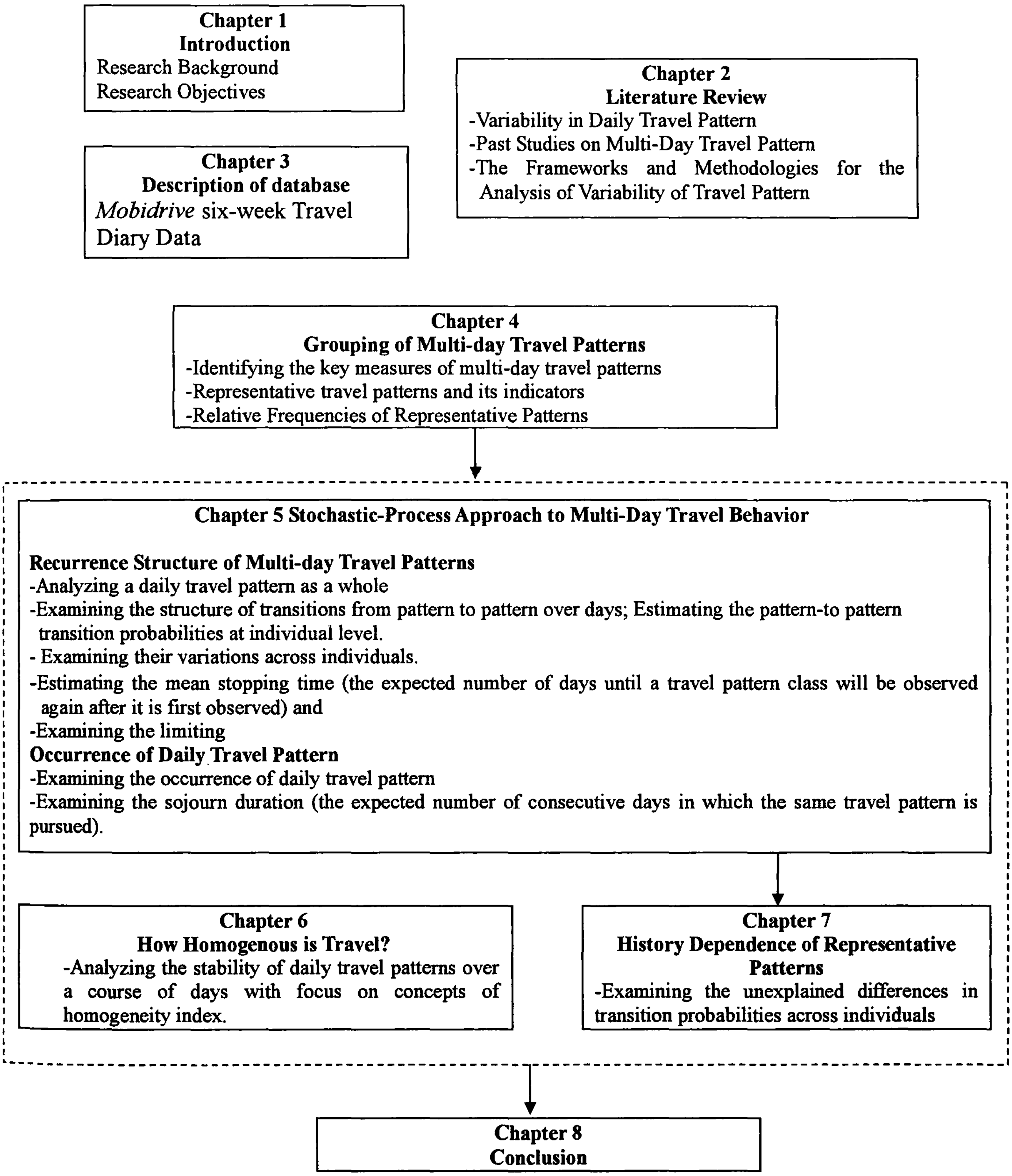


Figure 1.1 Outline of the Dissertation

TABLE 3.1 Contents of the Trip Diary Data (Main study)

CHAPTER 2

THE DAY-TO-DAY VARIATION IN TRAVEL BEHAVIOR

This chapter provides the literature review of past studies about variability in daily travel pattern and multi-day travel pattern. Then frameworks and methodologies for analysis variability of travel pattern are discussed. Referring to the objectives of this study as well as the finding of the past studies, the hypotheses of this study are presented in the last part of this chapter.

2.1 Variability in Travel Pattern

A number of studies have contributed to the characterization and understanding of the variability in travel behavior over multi-day periods. The attractive points of studying variability in travel behaviors are:

- The investigation of variability of daily travel pattern is urgent for transport planning and policy purposes.
- The examination of day-to-day variability in travel patterns provides useful information on dynamic of travel behavior over time and guidance on type of models that are likely to predict behavior better.
- Without information on day-to-day variability, it is impossible to determine exactly how much of the interpersonal variability in travel pattern is genuine, and how much is the

artifact of intra-person, day-to-day variability (Hanson and Huff, 1986).

- Furthermore, it is important to understand about the behavioral variability in order to address the broader issuers of the relationship between the individual/household and urban environment and in order to grasp the role of mobility in determining the quality of urban life. (Huff and Hanson, 1990).

Travel behavior researchers argue that there are two sources of day-to-day variability in travel pattern. First, variation in daily travel pattern occurs because the needs and desires of individuals are not constant from day to day. We do not repeat same things every day. There are trips that are highly routine and made regularly on a daily basis independent of other trips and activity engagements, and there are activities that are engaged in with longer intervals, such as weekly shopping. Also, there are activities that do not have particular cycles for engagement and take place in haphazard manners, such as a trip to a furniture store. Therefore, day-to -day variation in individuals needs as well as different needs across people have put the individual daily travel pattern into a dynamic process.

Second, travel behavior varies from day-to-day because feedback from transportation system. For example, if there was congestion yesterday on his usual route, one might change his route today for work trip.

The significance of day-to-day variability in travel behavior has been demonstrated by Pas and his colleagues (Pas, 1984; Pas and Koppelman, 1986; Pas, 1986; Pas, 1988; Koppelman and Pas, 1984). Pas (1988) distinguishes between inter-personal variability and intra-personal variability. Inter-personal variability refers to the variation in travel behavior across individuals, while intra-personal variability refers to the variation in behavior over time for a given individual. Note that most previous analyses of travel behavior in the literature are based on one-day data and address inter-personal variation in travel and attempt to systematically relate differences in behavior across individuals to differences in person and household attributes.

Using a Reading, UK, data set, Pas has shown that about 50 percent of the total variation in trip rate can be attributed to intra-personal, day-to-day variation. Importantly, the level of intra-personal variation varies significantly across demographic segments. For example, according to the results, females exhibit higher levels of intra-personal variability than do males, presumably due to the roles traditionally played by females in household.

Previous studies have also shown that individuals' travel patterns are characterized by both repetition and variability. For example, the series of studies by Hanson and Huff with the Uppsala household travel survey data (Hanson and Huff, 1982, Hanson and Huff, 1986;

Hanson and Huff, 1986; Hanson and Huff, 1988; Huff and Hanson, 1990) show that whereas some behaviors are very repetitious, they evidently do not recur as part of the same daily travel activity pattern; every day is not like every other day, and no one day is superior to other days to be the most representative day for the majority of individuals. They also note that observations made on a single day are not likely to represent the range of daily travel patterns exhibited by the individual over a more extended time period; and they reject the view that travel is highly routinized in the strict sense that every weekday looks much like every other weekday.

The notion of "typical" pattern (Hanson and Huff, 1988) has emerged as one of the key concepts in addressing the variability in daily travel pattern. Trips for some specific activities, such as grocery shopping and chauffeuring children, may be repetitive on a day-to-day or week-to-week basis. Hanson and Huff note that "An assumption that pervades theoretical and empirical work on urban travel behavior is that individuals' daily travel patterns are largely habitual and that these habitual patterns are remarkably stable in the short run" (Hanson and Huff, 1988). Yet, their results have shown that, over the five-week observation period, each person exhibited more than one typical daily travel pattern. The presence of multiple typical patterns for each individual implies that daily travel is not perfectly repetitious. At the same time, it suggests that day-to-day variation may be represented by transitions among multiple typical patterns. The analysis of this present study is based on this conceptualization of day-to-day variation in travel.

Pas (1988) also notes that behavior is repetitious, but the level of repetition is different for different aspects of travel behavior and also across socio-demographic groups, and that the types of behaviors that are most repetitious differ across groups. For example, Kitamura and van der Hoorn (1987) examine repetition in shopping participation. Their finding is that about 70 percent of the male workers and 59 percent of the female workers in a Dutch panel data set had identical daily patterns of shopping participation on five or more of the days of each of the two weeks that were compared. Huff and Hanson (1990), on the other hand, note that their "earlier results tend to run counter to the dominant trends in thinking in this area, and apparently contradict the conclusions of" Kitamura and van der Hoorn (1987). There appears to be little consensus in the literature on the variability and repetition of travel.

There are many reasons why consistent findings on variability and repetition are rare and far apart, if not non-existent at all, in the literature. To begin with, multi-day travel data sets are few and far apart, and those few multi-day data that are available are from a variety of countries, with different sample sizes, and with data collected in different formats and methods. In particular, the time span of the survey, or the number of days covered in the data, varies from a mere two days to one week to five or six weeks (some multi-day data are panel data with repeated multi-day observations of the same set of sample individuals typically with one-year intervals). Pas (1982) and Damm (1983) suggest that scheduling behavior over either a weekly or a monthly cycle be explored. The examination of cycles associated with various activities performed by an individual reveals that most common cycle is one week long, especially for non-home activities. Obviously, then, multi-day data must contain at least a few weeks worth of observation so that multiple weekly cycles can be examined. Not all empirical studies in the literature are based on such data.

Second, the aspect of travel behavior whose variability and repetition are examined, and how the behavioral aspect is quantitatively represented in the analysis vary from study to study. Third, modeling approaches and statistical methods adopted are different. For example, Brög (1980) argues that an individual's behavior is likely to vary in the short run because the environment within which travel takes place is likely to vary over time even in the short run. In Brög's view, observed behavior is, to a large extent, the result of constraints faced by the individual, and these constraints are likely to vary from day to day. A totally repetitive behavior would result only if the individual faces the same constraints every day, a situation which is highly improbable. This view would lead to an examination of the variability of constraints. One example can be found in Kitamura et al. (2005) where the variability of the departure time of the first trip in the morning is examined, using stochastic frontier models, in light of the variation in Hägerstrand's prism vertex location. The conclusion obtained was that prism vertex location is relatively stable over time, and departure time, given the vertex location, is highly variable. Then, one might find day-to-day variability limited after examining constraints, while he/she might conclude that variability is substantial after examining departure times. Likewise, a behavioral aspect may be examined to yield different conclusions from different conceptualizations or modeling approaches.

Again, the empirical findings that have been accumulated thus far are by no means consistent with each other. In addition to the points raised above, it is important to note that most of previous studies have narrowly focused on specific aspects of travel, e.g., trip rate, a particular trip purpose (e.g., shopping) or visits at a frequented location. It has been rare that the variability in daily travel patterns in their entirety is examined over a long span of time. Moreover, only limited knowledge exists on how different individuals exhibit different patterns of day-to-day variability.

2.2 Past Studies on Multi-Day Travel Patterns

Perhaps the most frequent reason that motivates multi-day study is the examination of variation in travel behavior over time. Earlier multi-day studies of travel pattern can be classified into three broad groups; first group use descriptive analysis technique to measure the extent of day-to-day variability in activity and travel characteristics (e.g., Pas, 1987; Pas and Sundar, 1995; Pendyala, 2000). For example Pas and Sundar (1995) find that considerable variation in trip frequency, trip chaining and daily travel time from three-day travel survey contacted in 1983 in Seattle, Washington. The result also indicate that the level of variation is very similar to those previously found could be found. The second group of multi-day analysis examines both extent of day-to day variability in activity-travel patterns as well as the influence of individual characteristics on extent of variability (see e.g., Herz, 1983; Bonsall et all., 1984; Huff and Hanson, 1986, 1990; Hanson and Huff, 1988, Pas and Koppelman, 1987; Mannering, 1987; Schlich and Axhausen, 2003). The last group accommodates unobserved heterogeneity across individuals. The studies of Kitamura (2003), Bhat (1999) contribute the significance and improvement of models including such unobserved heterogeneity in various types of travel behavior. The non-work stops with unobserved variation across individual analyzed by Bhat (1999). The data set used in this collected San Fransisco Bay Area. The results indicate that the proposed model provides a superior fit to the data relative to a model that ignores the unobserved variation. Using same data set Bhat (2000) examine unobserved heterogeneity in commute mode choice. The study Kitamura et al (2003) indicates that there is significant unobserved heterogeneity in prism vertices location.

2.3 Frameworks and Methodologies for Analysis Variability of Travel Pattern

The number of approaches has been proposed in these studies in order reveal day-to-day variability of travel patterns These include classificatory analyses that extract salient dimensions along which variations in daily travel patterns can be effectively captured (Pas, 1983, Pas, 1984; Koppelman and Pas, 1985; Recker et al, 1985), or apply sequencing schemes to reduce the dimensionality (Kitamura and Kermanshah, 1983, 1984). The classificatory methods have been extended to analyze multi-day travel patterns (Pas and Koppelman, 1985; 1986; Hanson and Huff, 1986; Hanson and Huff, 1986), or to enumerate feasible activity-travel patterns (Recker et. al, 1985). For example, Pas and Koppelman (1985; 1986) and Pas (1988) utilize their classification scheme of daily travel patterns to characterize a multi-day travel pattern in terms of the daily travel patterns it contains.

Segmenting population into groups with homogenous travel behavior has been important in travel analysis for a long time. This classification identifies groups of people with string similarities in their travel behavior, but clear distinctions from the member of other groups. One reason for plausibility of expecting to find distinguishable travel-activity patterns among different well-defined groups is intuitively reasonable notion that the long-term decision of individual and households systematically affect their short- term behavior. (Salomon, 1983; Cullen& Phelps, 1975). Pas (1984), for example, with data from Baltimore identified groups of individual on the basis of their one-day travel-activity patterns. Then, examine the effects of socio-demographic characteristics on daily-travel pattern. Recker and Schuler (1982) were able to identify homogenous groups of people. Past studies have found that socio-demographic and particularly role descriptors, are better discriminators of travel activity patterns, however still explain only a relatively small amount of the variation in behavior. (Herz, 1982; Rocker & Schuler, 1982; Wermuth, 1982; Kutter, 1973; Pas, 1984; Hanson, 1982). This is particularly surprising because those classifications are unsatisfactory; they explain only a small amount of variability within groups. Two different issues contribute to this shortcoming: first, the lack of suitable longitudinal data, the second, with two components, is the way similarity is measured and how order of activities is considered in the measurement.

Recker and Schuler (1980) developed a way to classify such time space paths by using pattern recognition techniques. Transformations are used first to simplify the space-time path, and then similar paths are clustered on the basis of selected characteristics of paths. This method emphasis the locations of the individual in space and time throughout a given day, but it does not permit such as mode used or activity participation to be considered simultaneously with space-time coordinate. Recker et al (1986) used the combination of simulation approach (STARCHILD: Simulation of Travel/ Activity Responses to Complex Household Interactive Logistic Decision.) with techniques of pattern recognition, multi-objective optimization and disaggregate choice model to examine household travel/activity pattern.

Multi-dimensional sequence alignment which consider not only type of activities performed, but also their order and timing. The result based on the longitudinal Mobidrive data show that intrapersonal variability is quite high. The result also shows that the members of each cluster are very similar in term of daily activity programs, but dissimilar in terms of socio-demographic indicators.

Hirsh et al (1986) analyzed weekly travel pattern by utility maximizing theory. In this study, they defined an activity program as the collection of all the activities undertaken during a certain period of time, independently of the order of their occurrence. A dynamic decision-making process suggested whereby the individual's decision is made at the beginning of each period of the week. Recker et al (1986) proposed theoretical framework that positioning the individual as the decision maker who implements activity programs integrating various scheduling rules, available resources and a multitude of constraints. This process is depend on basic concepts of utility maximization within a constrained environment and results in observed travel/activity behavior.

Jianya Zhou and Reginald Golledge (2000) applied MONOVA and discriminant analysis method to analyze day-to-day activity variability across the week. With GPS-collected data, two physical measurement of trips (time duration and frequency) are analyzed to discriminate how people's activities show different patterns among days in a week in terms of activities pursued.

Using 6-weeks travel diary undertaken in Germany, Frusti et al (2003) analyzed individual activity-travel pattern with fixed commitment concept. The fixed commitments are defined as activities that occur on regular schedule. The agenda of fixed activities is established by Kitamura and Fujii (1998).PCATS (The Prism-Constrained Activity-Travel Simulator was based on dividing the day into two types of period: "open" period and "blocked" periods. Open period's represents times of day when an individual has the option of traveling and engaging in "flexible" activities. "Blocked" periods represent times when an individual is committed to performing "fixed" activities.

For addressing the problem of variability of travel behavior, various measures have been used. Total trip rates or vector of descriptive attributes (number of journeys, number of stops, travel mode used, duration of journeys, etc) have been used to compare activity pattern by Koppelman & Pas (1984) and Hanson and Huff (1982). Huff and Hanson (1986) developed a number of measures all based upon the ordered set of trips links (or stops) that constitute the individual's *n*th the daily travel pattern. The most important finding is that individual exhibit more than one characteristics or archetypical daily pattern, and these patterns are fundamentally different from each other as evidence by the distinct core patterns associated with each of various representative days.

Hanson and Huff (1982) focused on complex travel-activity patterns and thus their research has had to deal with difficult definition and measurement. They found that the level of day-to-day variability depends to some extent on the definition and measurement employed in describing behavior and variability.

Mahmassani et al. (1991) examine day-to-day variability in trip chaining, departure time from home, route choice for morning work commute using data obtained from Texas. In this research intrapersonal variability measured and defined in two different ways. Methods: 1. "day-to day" approach the behavior of each commuter is examined to see if the departure time from home and route through the network on a given day are different from that on previous day 2. "deviation from usual" approach-examines deviation from median departure time and the most commonly chosen route as measures of intrapersonal variability.

Pas (1980) has pursued a stop-based measurement approach to classify travel-activity pattern. For each daily pattern, Pas develops a descriptor that basically counts the number of ways in which two stops are similar and then sum over the number of stops in the pattern. Pas(1987) examined day-to-day variability in daily trip rates. In this work, the variance in an individual's daily trip rate about his/her daily average was used as a measure of intrapersonal variability.

Koppelman and Pas (1984) (study about intrapersonal variability) examination of issues in estimating linear least- square regression in trip generation models using the repeated observation on set of sampling unit. The model they describe is a special case of the general class of model that combines cross sectional and longitudinal data and it can be estimated using generalized least squares. Pas (1987) investigate the effects of day-to day variability on goodness- of- fit of least squares regression models of person trip generation. The analytic result show that the conventional R square goodness of fit measure for least squares regression models estimated with cross-sectional data is dependent upon two factors. The first factor is the proportion of the between-person variability that is accounted for by the explanatory variables in the model. The second factor is the proportion of the total variability in the dependent variable that is due to between-person variability. Most importantly, this research show that the existence of intrapersonal variability leads to lower estimates of the goodness- of-fit.

Another groups of researchers have adopt the concept of prism to examine day-to-day variation in travel behavior. (Kitamura et al, 2000b; Pendyala et al, 2002 Yamamoto et al, 2004). An individual's daily travel is constrained by time-space prisms as much as it is driven by the needs and desires of the individual and household. The variability of a prism vertex location implies that how the timeframe of the individual's daily activity schedule varies from day to day. It represent that individual daily travel pattern varies from day to day.

On the other hand, Jones and Clarke (1988) calculated similarity index, which divides the day in temporal intervals and compares the chosen activities of two days within the same interval. Similarity index value 0 indicates those two daily travel patterns have nothing in common while value of 1 imply identical activity patterns. Schlich and Axhausen (2003) note the disadvantage of this model as it ignores other attributes such as transport mode which is important for transport planning.

The discussions and finding of past studies indicate that variations in the extent of day-to-day variability depending on the specific measures of variability used, travel characteristics examined and data sets employed, it is clear that day-to-day variability in travel behavior exists and is substantial.

2.4 The Hypotheses of the Study

It well recognized that the variation in individual daily travel result variation in the needs and desires which individual attempts to satisfy and affected by the travel resources and time constraints which limit the individual's freedom to vary behavior from day to day.

Some trips are made highly routine and made regularly on daily basis independent other trips and activity engagement, like working and studying. There are activities that engaged less frequently, engaged with longer intervals such as weekly shopping. Also, there are activities that do not have particular cycles for engagement and take place in haphazard manners, such as a trip to a furniture store.

These considerations lead to the following hypothesis that conceivable in examining the variability of individual daily travel pattern over time and heterogeneity across individual in the term of multi-day travel pattern.

- The day-to-day variation in daily travel patterns highly depends on an individual's daily routine as well as their work/residence locations.
- Pattern-to pattern transition probability will vary across individuals, i.e., there will be higher level of heterogeneity across individual in the day-to-day variation of their travel patterns.

Chapter 3
Description of the Database

It is clear that multi-day travel data would be able to offer information on the stochastic nature of daily travel patterns. In this study, individuals' multi-day travel patterns are analyzed using the Mobi*drive* data set that contains travel records obtained from a continuous six-week travel diary survey. This chapter describes dataset and the profiles of the samples.

3.1 *Mobidrive* Six-weeks Travel Diary Data

The *Mobidrive* survey is a continuous six-week travel diary survey that was conducted in the German cities of Halle and Karlsruhe in spring and autumn 1999, funded by the German Federal Ministry of Education and Research. The survey was carried out with the aim to obtain a more detailed picture of mobility patterns and to develop methodological approaches to capture behavioral variability.

A total of 317 persons over six years age from 139 households participated in the main phase of the survey, after testing the survey instruments in a pre-test with a smaller sample in spring 1999. Sampling procedures, survey instruments, and data administration are presented in Axhausen, Zimmermann, Schönfelder, Rindsfüser and Haupt (2002).

The data set is documented in Schönfelder, Schlich, König, Horisberger and Axhausen (2000) and available for download at http://129.132.96.89/index .html. The survey contains the following information including;

- Six-week continuously travel diary
- Personal values as well as attitudes towards the different modes of transport
- Household and individuals' socio-demographic characteristics
- Commitments to specific regular activities

In addition, in order to facilitate the analysis of variability in spatial behavior over time, Mobi*drive* provide exact locational data. The precise locational data was obtained by geocoding the trip destination addresses of all main study trips. The addresses including home and workplace locations were transformed into Gauss-Krüger coordinates in a WGS 84 (World Geodetic System) geodetic reference system.

Description of Study Areas:

Halle

Its approximately 240 000 inhabitants and administrative area of 135 km make Halle the largest city in Saxony-Anhalt and fourth largest in the East of Germany. The city lies on the banks of the river Saale and is fortunate in its transport connections: the Leipzig/Halle airport, the junction of the A9 and A14 motorways (superhighways), Intercity rail connections, the port on the Saale at Trotha. Its well-established university and other college-level institutions have about 16,000 students. While the city is recovering from a particularly massive restructuring of its once dominant chemical industry, it still has an above-average rate of unemployment of about 22 %. This partially reflects the very high of labor force participation in the old East Germany economy.

Karlsruhe

Karlsruhe is the second largest city in the Federal State of Baden-Württemberg, in Germany. The city lies in the heart of Europe, at the foot of the Black Forest and next to the Rhine River. Located in the economic powerhouse of the state of Baden-Würtemberg, With about 300.000 inhabitants is the center for shopping and cultural events for a region of about one million people. Today, Karlsruhe is home to two Supreme Courts, the Federal Constitutional Court and the Federal Supreme Court.

The samples are recruited through a telephone screening and recruitment process. The contents of the trip diary data of the main survey can be seen on Table 3.1. The contents of household, individual and vehicle questionnaires can be seen on Appendices A.1, A.2 and A.3, respectively. The *Mobidrive* complete questionnaires can be seen at PTV AG et al. (2000) and the detail description of each variable's imputation, analysis processes and statistical distributions can be found at Schönfelder et al. (2002).

TABLE 3.1 Contents of the Trip Diary Data (Main study)

Item	Coding and Comments
Day of trip	Days of the week
Starting time	Military time
Purpose	- work - education - daily shopping - shopping for major items - personal business - work related business - leisure (please specify) - other (please specify)
Modes used	- walk only - walk to mode - bicycle - motorcycle - car driver - car passenger - bus - street car and light rail - heavy rail - other (please specify) - walk from mode - time spent on each
Accompanying person	- Number of household member - number of other persons
Presence of a dog	Yes no
Exact destination	Street address and municipality
Activity costs	- Zero, up to 10 DM - 10 – 25 DM - 25 – 100 DM - 100 DM and over
Expenditures on travel	Open
Arrival time	Military time
Estimated distance traveled	[m]

Source: Axhausen et al., 2002

3.3 Survey Results

The number of reported movements and days are shown in Table 3.2. The samples' profiles of the *Mobidrive* main survey, which used as basic database in subsequent analyses, are shown in Table 3.3.

TABLE 3.2 The Number of Reported Movements and Days

Contents	Pre-test	Main Study	
	Karlsruhe	Halle	Karlsruhe
Trips	6,741	30,549	38,152
Journeys	2,801	9,323	10,210
Long-distance journey days	113	214	329
Activities	6,785	21,150	24,699
Person days *	1,725	6,378	6,257
Immobile days	100	593	267
Missing days	10	44	92

* The number of person days includes the number of immobile days

Source: Axhausen et al., 2002

TABLE 3.3 Sample Profiles of the *Mobidrive* Main Survey

	Descriptor of Daily Travel Patterns	Sample Average
	Group 1: Mobility Measures	
1	Number of trips on the day	4.14
2	Number of visits on the day	2.41
3	Number of trip chain on the given day.	1.71
4	Total travel time on the given day	76.4
5	Average travel time (duration) per trip on the day (minutes)	20.2
6	Proportion of trips with co-travelers	0.17
7	Number of long trips (> 100 km) on the day	0.004
.	Group2: Trip Purposes	
8	Proportion of work visits in the total visits of the day	0.155
9	Proportion of school visits	0.073
10	Proportion of shopping visits	0.117
11	Proportion of leisure and social visits	0.191
	Group 3: Time Expenditures for Out-of-home Activities	
12	Total time expenditure for out-of-home activities on the day (minutes)	414.7
13	Proportion of work duration in the total out-of-home activity duration	0.368
14	Proportion of school duration	0.181
15	Proportion of shopping duration	0.150
16	Proportion of leisure and social activity duration	0.278
	Group 4: Travel Mode	
17	Fraction of private car (including motorcycle) trips in all trips on the day	0.433
18	Fraction of public transport trips	0.184
19	Fraction of bicycle trips	0.134
20	Fraction of walk trips	0.245
	Group 5: Spatial Extension of Daily Travel	
21	Average trip duration (minutes)	20.3
22	Total travel distance on the day (km)	28.2
23	Proportion of destinations located within 1.0 km from home	0.204
24	Proportion of destinations located between 1.0 – 5.0 km from home	0.447
25	Proportion of destinations located more than 5.0 km from home	0.349
	Group 6: Situational Factors	
26	Average size of travel party on the day	1.44
27	Average monetary expenditure per trip on the day (DM)	8.37
28	Proportion of trips between 6 a.m. and 10 p.m.	0.957
29	Proportion of trips between 10 p.m. and 6 a.m.	0.043
	N (person-days)	8501

Chapter 4
Grouping the Multi-Day Travel Pattern

The objective of this chapter is to identify a small number of classes of daily travel patterns using these measures available from the *Mobidrive* data set. This is done by applying principal component analysis (PCA) in two steps, then applying *k*-mean cluster analysis. In the following section methodology of identifying the key measures of multi-day pattern described. Results of k mean cluster analysis is then presented and will used in following the subsequent analysis.

- Recurrence Structure of Daily Travel Pattern; Occurrence and Sojourn Duration of Representative Patterns (Chapter 5)
- Who Has a Homogeneous Travel Pattern Over Days and Who Does Not? (Chapter 6)

4.1 Identifying the Key Measures of Multi-day Travel Patterns

The individual's activity travel patterns cannot be described by only one certain parameter, but it is complex relationships between individual's socio demographic conditions, travel environments, constraints, and resources which are unique for each time frame and each individual. However, directly using several dozen of variables to analyze travel behavior would probably leading to bias results due to high correlation between variables.

It is proposed that multi-day travel patterns be represented as a composite of daily travel pattern classes, which are so defined as to be interpretable and reflect the many aspects of daily travel patterns, rather than to simply maximize the fraction of variance explained. The method adopted here is to classify observed daily travel patterns into a small number of classes by applying principal component analysis (PCA) in two steps, then applying k-mean cluster analysis.

The basic procedure in principal component analysis are as follows (Manly, 1986; Washington et. al, 2005): standardize all observed variables in the observation matrix; calculate the variance-covariance matrix, which is the correlation matrix after standardization; determine the eigenvalues and corresponding eigenvectors of the correlation matrix (the parameter of the ith principal component are given by the eigenvector, where as the variance is given by the eigenvalue); discard any components that account for a relatively small proportion of the variation in the data.

In first step of PCA, the behavior information obtained from *Mobidrive* dataset was organized into a matrix I_1 so that the matrix pattern of the observed individual was represented by a row of numerical values. Matrix I_1 contains 8506 rows and 29 columns.

Using SPSS version 13, the distribution of the variance that explained by eigenvalues are calculated. Only those components that have eigenvalues greater than 1 are considered as significant. Based on the significant components obtained from the PCA analysis, internally homogenous subgroups of daily travel patterns are sought with a k-means clustering algorithm.

In the first step, the 29 descriptors of daily travel patterns are grouped into six as shown in Table 3.3, and PCA is applied to each of the six groups of descriptors. A total of 15 factor components representing the six groups are selected for use in the second step (Table 4.1). These are:

Two factors from Group 1, Mobility Measures (66.4%)
Three factors from Group 2, Trip Purposes (94.4%)
Three factors from Group 3,Time Expenditures for Out-of-home Activities (92.7%)
Three factors from Group 4, Travel Mode (99.9%)
Two factors from Group 5, Spatial Extension of Daily Travel (65.1%)
Two factors from Group 6, Situational Factors (52.1%) where the percentage figure in

Table 4.1 Results of 'Step 1'- PCA Analysis; Total Variance Explained

	Descriptor of Daily Travel Patterns	Initial Eigenvalues	
		Total	% of Variance
	Group 1: Mobility Measures		
1	Number of trips on the day	**2.69**	38.4
2	Number of visits on the day	**1.96**	66.4
3	Number of trip chain on the given day.	0.98	80.7
4	Total travel time on the given day	0.72	90.9
5	Average travel time (duration) per trip on the day (minutes)	0.54	98.7
6	Proportion of trips with co-travelers	0.09	100
7	Number of long trips (> 100 km) on the day	0	100
.	Group2: Trip Purposes		
8	Proportion of work visits in the total visits of the day	**1.41**	35.2
9	Proportion of school visits	**1.24**	66.1
10	Proportion of shopping visits	**1.13**	94.4
11	Proportion of leisure and social visits	0.23	100
	Group 3: Time Expenditures for Out-of-home Activities		
12	Total time expenditure for out-of-home activities on the day (minutes)	**2.09**	41.8
13	Proportion of work duration in the total out-of-home activity duration	**1.34**	68.7
14	Proportion of school duration	**1.20**	92.7
15	Proportion of shopping duration	0.34	99.6
16	Proportion of leisure and social activity duration	0.02	100
	Group 4: Travel Mode		
17	Fraction of private car (including motorcycle) trips in all trips on the day	**1.59**	39.8
18	Fraction of public transport trips	**1.20**	69.9
19	Fraction of bicycle trips	**1.20**	99.9
20	Fraction of walk trips	0	100
	Group 5: Spatial Extension of Daily Travel		
21	Average trip duration (minutes)	**2.16**	43.2
22	Total travel distance on the day (km)	**1.09**	65.1
23	Proportion of destinations located within 1.0 km from home	0.84	82.0
24	Proportion of destinations located between 1.0 – 5.0 km from home	0.64	94.9
25	Proportion of destinations located more than 5.0 km from home	0.26	100
	Group 6: Situational Factors		
26	Average size of travel party on the day	**1.06**	26.5
27	Average monetary expenditure per trip on the day (DM)	**1.03**	52.1
28	Proportion of trips between 6 a.m. and 10 p.m.	0.97	76.4
29	Proportion of trips between 10 p.m. and 6 a.m.	0.94	100
	N (person-days)	**8501**	

parentheses indicates the fraction of total variance explained within each group.

PCA is applied to these 15 factors in the second step. The resultant first six factor components collectively account for 78.2 percent of the total variance, and are used in the subsequent analysis. These six factors may be described as:

-Component One (*Obligatory Activity Engagement)* is defined primarily by: proportion of work duration, proportion of work visits, proportion of school visits, and proportion of school duration

-Component Two (*Shopping Engagement)*: proportion of shopping visits and the number of trips on the day

-Component Three (*Activity Intensity*): number of trips, number of visits, and total out-of-home activity time expenditure

-Component Four (*Spatial Extension*): total travel distance and average trip duration.

-Component Five (*Car and Public Transport Use)*: fraction of public transport trips and fraction of private car (including motorcycle) trips

-Component Six (*Bicycle Use*): fraction of bicycle trips.

4.2 Representative Patterns and Their Pursues

A k-means clustering algorithm (SPSS 13) partitioned the 8506 cases into five groups. This yielded the five representative pattern groups (hereafter called simply "representative patterns") shown in Table 4.2, which are used in the subsequent analysis. The salient features of daily travel patterns contained in the representative patterns are described as (observed frequency of daily patterns in parentheses):

-Pattern A (1915) *Public Transport Commuting:* involves commuting by pubic transport

-Pattern B (710) *Car-based Multiple Visits*: multiple trips and typically three or four visits, a car is used extensively

-Pattern C (1953) *Shopping & Leisure*: typically three or four trips per day for shopping and other non-work purposes with time expended for shopping, leisure and social activities

-Pattern D (1790) *Accompanying*: a higher fraction of chauffeuring passengers

-Pattern E (2138) *Work*: comprising mostly work visits with time spent on work-related activities.

Table 4.3 shows the socio-demographic descriptors of the individuals who pursued the respective representative patterns. The statistics are weighted by the frequency of pursuing each pattern during the survey period; if an individual pursued a pattern n times in the record, his/her socio-demographic attributes are weighted by n. Each pattern tends to be pursued by a

TABLE 4.2 Descriptive Statistics of Travel Characteristics of Each Representative Pattern

Sample Size =8506	Representative Patterns of Daily Travel									
	Pattern A Public Transport Commuting (N = 1915)		**Pattern B** Car based Multiple Visits (N = 710)		**Pattern C** Shopping & Leisure (N = 1953)		**Pattern D** Accompanying (N = 1790)		**Pattern E** Work (N = 2138)	
Variable	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviatio n
Number of trips on the day	4.27	2.18	4.99	2.25	3.52	1.72	4.25	2.19	4.23	1.97
Number of visits on the day	2.48	1.60	3.15	1.82	1.85	1.09	2.46	1.53	2.56	1.54
Proportion of work visits	0.17	0.21	0.26	0.17	0.02	0.09	0.08	0.15	0.29	0.21
Proportion of school visits	0.13	0.17	0.03	0.08	0.01	0.06	0.13	0.20	0.05	0.11
Proportion of shopping visits	0.08	0.13	0.04	0.09	0.24	0.21	0.11	0.15	0.07	0.12
Total time expenditure for out-of-home activities	477.1	44.4	797.1	77.9	95.0	55.7	305.9	55.5	614.9	43.4
Proportion of work duration	0.39	0.45	0.63	0.32	0.04	0.17	0.20	0.36	0.70	0.39
Proportion of school duration	0.34	0.41	0.08	0.19	0.02	0.12	0.30	0.44	0.12	0.27
Proportion of shopping duration	0.05	0.10	0.02	0.06	0.47	0.44	0.11	0.22	0.03	0.07
Proportion of leisure and social activity duration	0.21	0.29	0.26	0.21	0.43	0.43	0.36	0.40	0.14	0.22
Fraction of private car (inc. motorcycle) trips	0.36	0.41	0.58	0.41	0.41	0.44	0.41	0.42	0.49	0.43
Fraction of public transport trips	0.25	0.37	0.16	0.29	0.10	0.26	0.19	0.34	0.21	0.34
Fraction of bicycle trips	0.17	0.32	0.13	0.27	0.11	0.29	0.15	0.31	0.11	0.27
Fraction of walk trips	0.22	0.32	0.13	0.22	0.37	0.41	0.25	0.35	0.19	0.29
Proportion of trips with co-travelers	0.14	0.25	0.11	0.20	0.21	0.35	0.23	0.33	0.11	0.21
N (person-days)=8501										

TABLE 4.3 Socio-Demographic Characteristics of Pursuers of the Five Representative Patterns†

Socio-demographic measures Sample Size =8506		Pattern A Public Transport Commuting (N = 1915)	Pattern B Car based Multiple Visits (N = 710)	Pattern C Shopping & Leisure (N = 1953)	Pattern D Accompanying (N = 1790)	Pattern E Work (N = 2138)
Male [D]		0.49	0.67	0.44	0.42	0.61
Age	Below 24 years old [D]	0.43	0.27	0.10	0.37	0.22
	25-34 years old [D]	0.07	0.13	0.08	0.07	0.16
	35-44 years old [D]	0.15	0.28	0.2	0.16	0.24
	45-54 years old [D]	0.22	0.18	0.16	0.14	0.24
	55-64 years old [D]	0.11	0.15	0.23	0.17	0.13
	Over 65 years old [D]	0.028	0.0014	0.24	0.08	0.007
Driver's license holding [D]		0.54	0.89	0.71	0.57	0.78
Worker [D]		0.31	0.68	0.16	0.14	0.66
Student [D]		0.36	0.10	0.07	0.35	0.15
Non-worker [D]		0.12	0.03	0.64	0.30	0.05
Married [D]		0.41	0.50	0.66	0.45	0.57
Family with school-age children [D]		0.44	0.30	0.23	0.46	0.36
Number of household members		3.15	2.71	2.5	3.02	2.91
Number of vehicles available		1.38	1.51	1.20	1.33	1.40
Number of telecommunication connections		2.46	2.84	2.25	2.47	2.66
Household income [x1,000 DM]		4.73	4.54	3.83	4.48	4.66
Live in CBD [D]		0.04	0.04	0.07	0.05	0.07
Live in inner city area [D]		0.26	0.32	0.33	0.25	0.27
Live in suburbs [D]		0.70	0.64	0.60	0.70	0.65
N (person-days)=8501						

† The table shows the sample means of the respective variables.

[D]: A 0-1 dummy variable which takes on a value of 1 when the condition given as the variable name is met. Thus the sample mean shown indicates the relative frequency of the cases where the condition is met.

group of individuals who may be characterized as:

Pattern A *Public Transport Commuting*: larger fractions of young people, people from large households, high income households, suburban households, and/or households with school-age children

.

Pattern B *Car-based Multiple Visits:* larger fractions of working people, those aged between 35 and 44 years, with a driver's license, from households with a larger number of vehicles, and/or households with frequent telecommunications connections

.

Pattern C *Shopping & Leisure:* larger fractions of individuals over 55 years old, non-workers, married people, and/or those who live in CBD and inner city area

.

Pattern D *Accompanying:* similar to pursuers of Pattern A, with a higher fraction of non-workers is higher in Pattern D than in Pattern A

.

Pattern E *Work*: larger fractions of workers and those between 25 and 54 years old. The five representative patterns have been produced based on the six components from the PCA analysis, and the key descriptors of each pattern have been identified based on travel-behavior and socio-demographic indicators. The results show that daily travel patterns may be grouped into a small set of classes while retaining much of the information in the original travel patterns.

Multi-day travel patterns are conceived as a sequence of these representative patterns (can be seen on Appendix B.1, B.2) and transition among the patterns over a course of six-weeks are analyzed with the framework of Markov Chain models in Chapter 5.

4.3 Relative Frequencies of Representative Daily Patterns

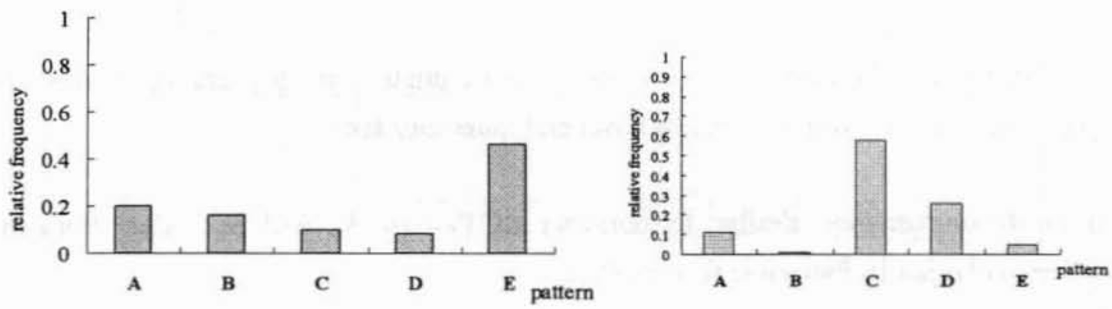
This section has devoted to describe the difference in daily travel pattern between workers and non-workers. Differences in daily travel pattern between workers and non-workers can be roughly observed by sequences of representative pattern over six-week period. (see, Appendix B1, B2).

Survey respondents who reported themselves as full time worker in Germany have their work hours ranging from 35 to 60 hours per week. Therefore, the sample is divided into three groups based on their work hours: first groups consists of 109 individuals who worked at least 35 hours per week, the second groups contains 122 individuals who worked less than 35 hours per week and third group comprises 86 individuals those not employed.

Hereafter, first group called "*workers*" (109) and third group will called "*non-workers*" (86) and differences in multi-day travel pattern between these groups are examined in this study.

Whole Workers/ Non-Workers

The relative frequencies of representative patterns for whole workers and non-workers are presented in Figure 4.1. The relative frequency of each pattern represents its empirical probability.



A. Workers B. Non-workers

Figure 4.1 Relative Frequencies of Representative Daily Patterns

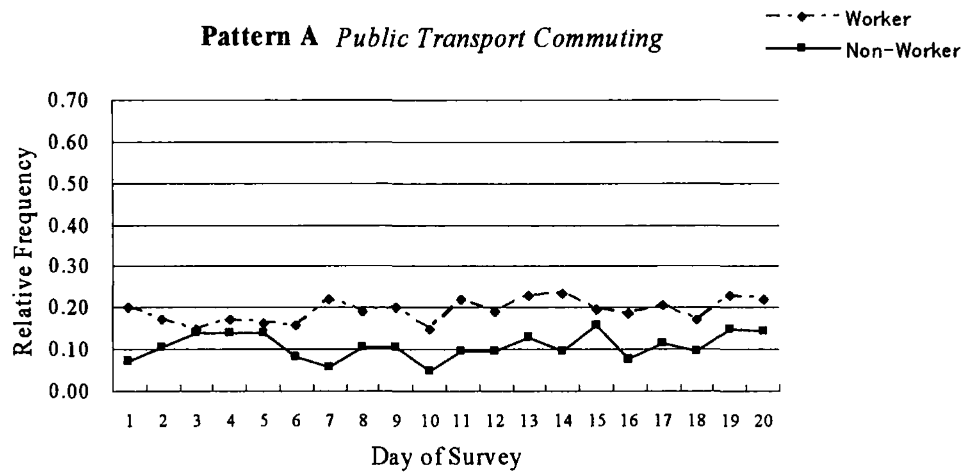
For workers, Pattern E *Work* is dominant, but Pattern A *Public Transport Commuting* and Pattern B *Car-based Multiple Visits* are also prevalent. For non-workers, Pattern C *Shopping & Leisure* is predominant, while Pattern D *Accompanying* is also frequent. Note that non-workers hardly engage in Pattern B *Car-based Multiple Visits*.

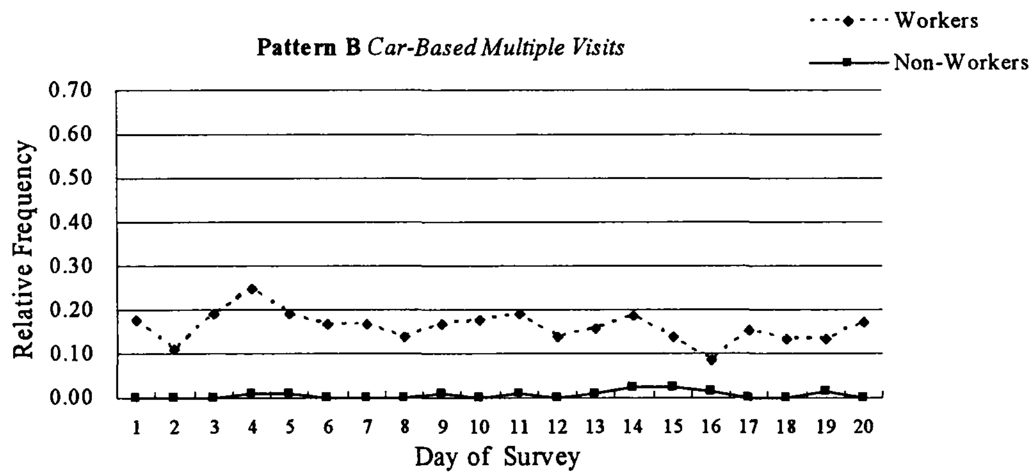
For workers, Pattern E *Work* is dominant, but Pattern A *Public Transport Commuting* and Pattern B *Car-based Multiple Visits* are also prevalent. For non-workers, Pattern C *Shopping & Leisure* is predominant, while Pattern D *Accompanying* is also frequent. Note that non-workers hardly engage in Pattern B *Car-based Multiple Visits*.

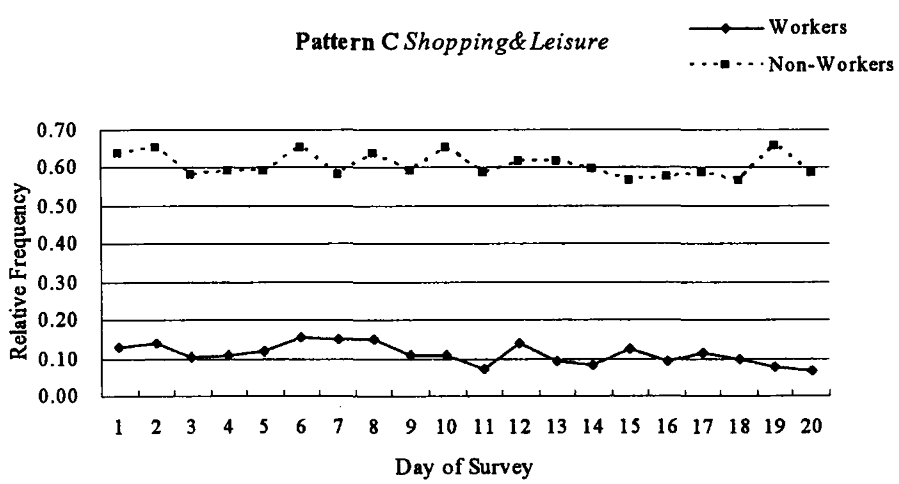
Day to day variations in relative patterns can be seen from Figure 4.2 and present that relative frequencies of representative patterns substantially vary from day to day and considerable different between workers and non-workers.

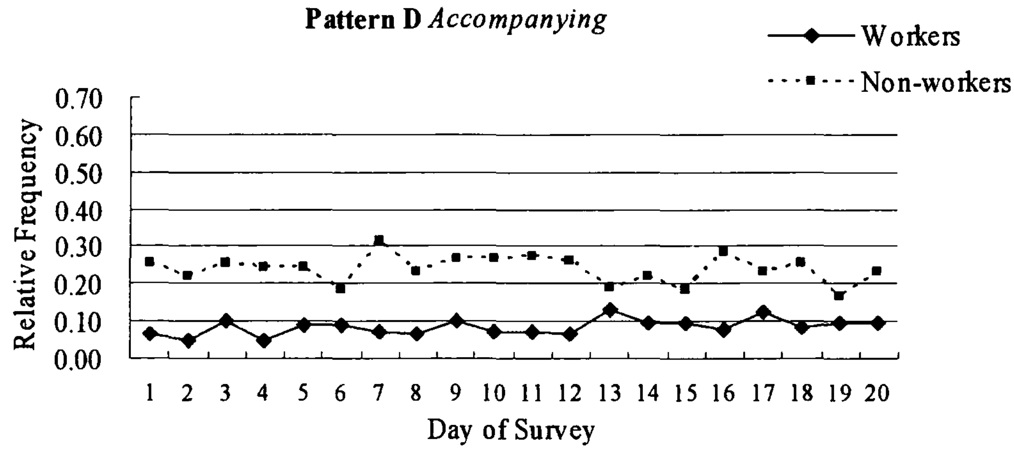
As workers tend have fixed obligatory trips and activity on weekday, the relative frequency of Pattern A *Public Transport Commuting*, Pattern B *Car-based Multiple Visits* and Pattern D *Accompanying* are relatively stable over survey day. Pattern E *Work* is highly dominant and varies from day to day.

Although, non-workers do not have obligatory trips, Pattern C *Shopping & Leisure* dominant from day to day and the tendency of Pattern B indicate that Pattern B *Car-based Multiple Visits* tend to be homogenous, non-workers less likely engage in Pattern B.









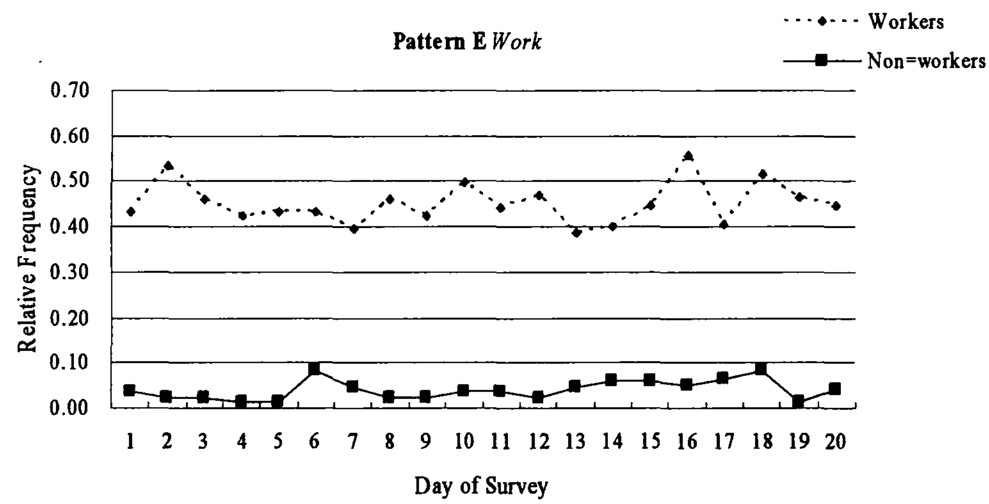


Figure 4.2

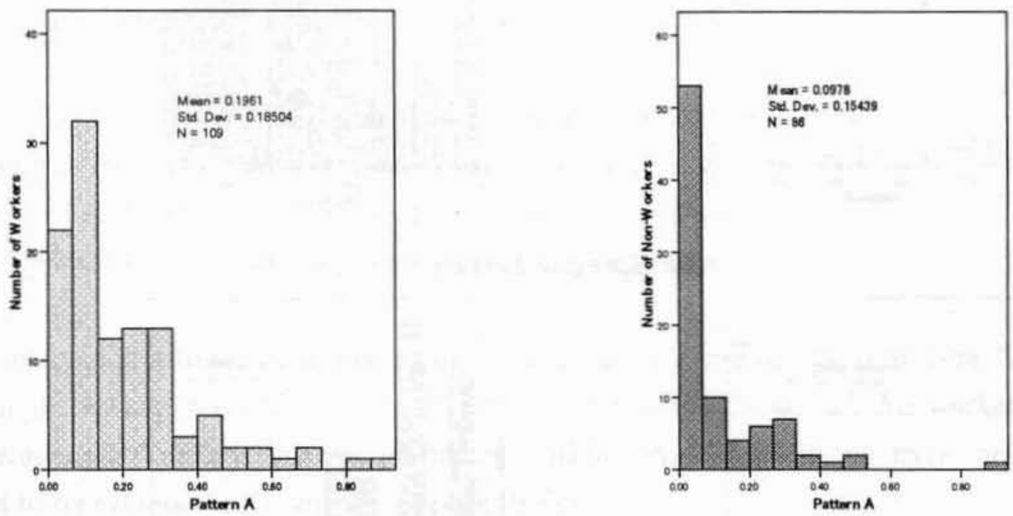
Relative Frequencies of Representative Daily Patterns by Day of Survey and Employment Status.

Individual-based Distribution of Daily Travel Patterns

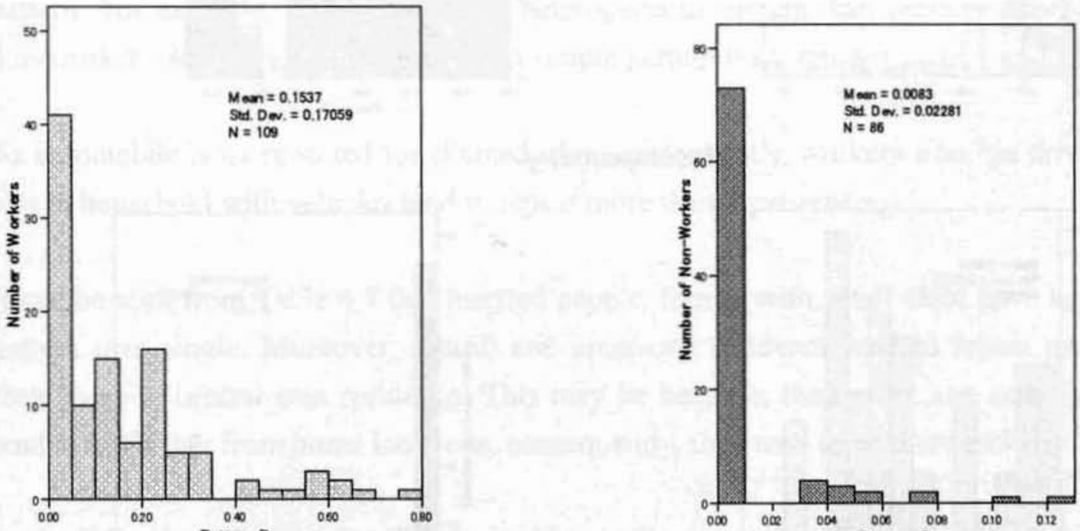
Differences in behavior across individual now examined. Figure 4.3 presents the occurrence of representative patterns varies substantially from individual to individual, and is quite different between workers and non-workers as well.

In general, the frequency distributions show that workers and non-workers are both quite heterogeneous internally as a group in term of the distribution of daily travel patterns they pursue. Particularly, the empirical probability of Pattern E *Work* varies substantially across workers. Those, Pattern A *Public Transport Commuting,* Pattern B *Car-based Multiple* also vary considerably from worker to worker.

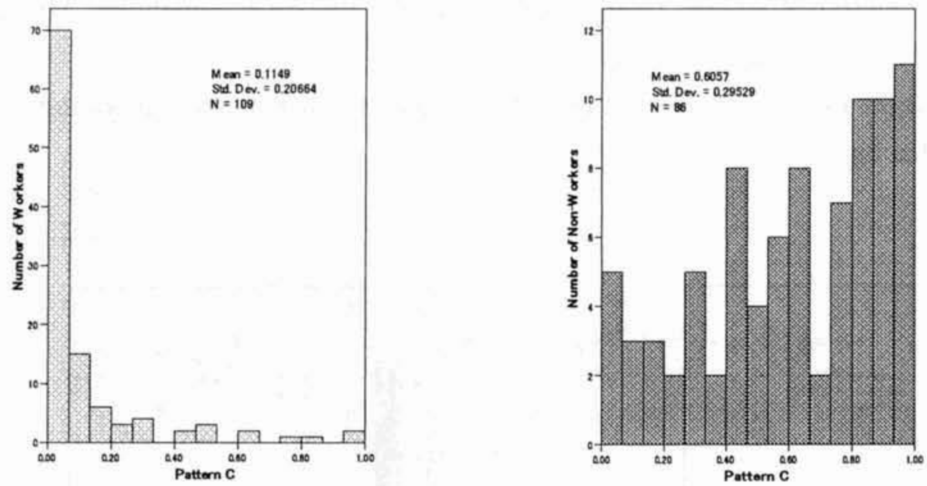
Non-workers, on the other hand, exhibit large heterogeneity for Pattern C *shopping & Leisure* and Pattern D *Accompanying.*



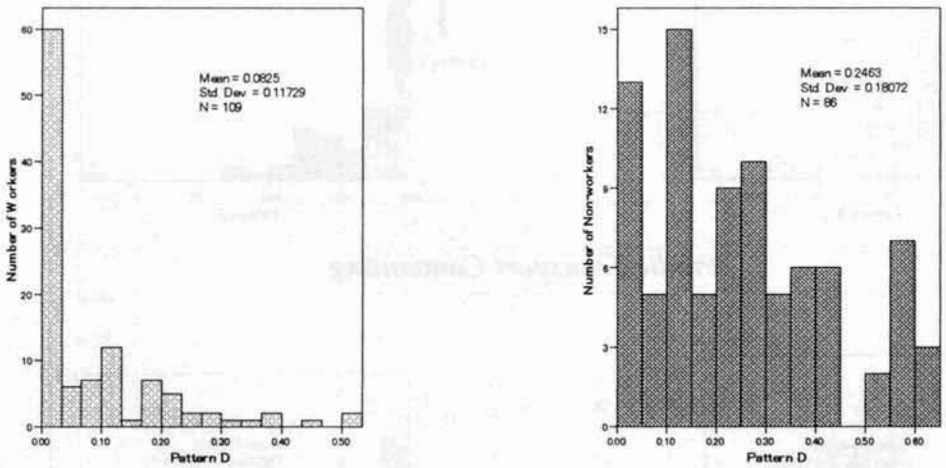
Public Transport Commuting



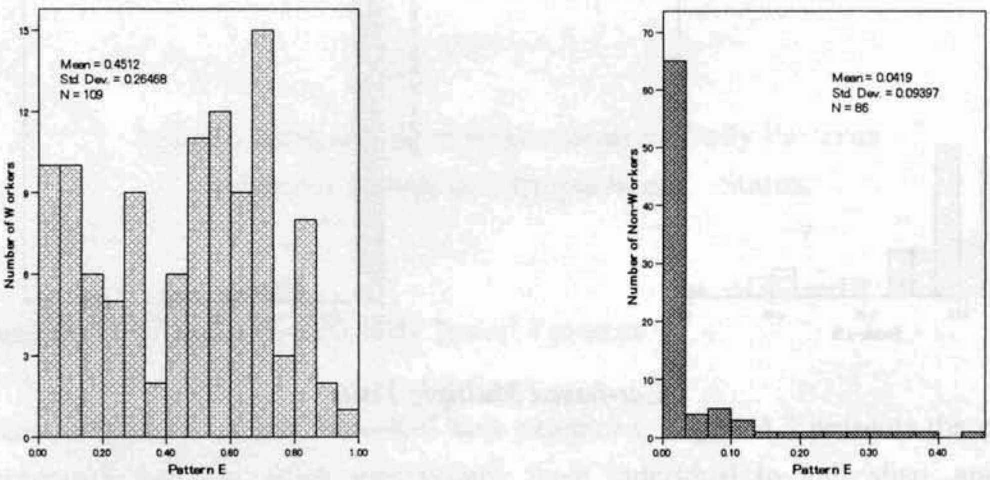
Car-based Multiple Visits



Shopping & Leisure



Accompanying



Work

The figures on the left show distribution of relative frequencies for workers, and those on the right show the relative frequencies for non-workers.

Figure 4.3 Individual-Based Relative Frequencies of Representative Daily Patterns

Identifying Homogenous Groups of People

This section identifies groups of people with string similarities in their travel behavior based on frequencies of representative patterns over 6-week period.

Four-groups of people identified in Table 4.4, those who repeat same pattern over 6-week period. Description of each group described as:

-*Group 1*- Individuals who repeated 1 or 2 types of patterns over 30 days
-*Group 2*- Individuals who repeated 3 patterns over 30 days
-*Group 3*- Individuals who repeated 4 patterns over 30 days
-*Group 4*- Individuals who repeated 5 patterns over 30 days

An interesting difference between workers and non-workers can be seen from Table 4.4. For example workers seem to repeat more than 3 patterns, which indicate that workers have more heterogeneous pattern than non-workers. Although, non-workers have simple patterns tend to repeat less than 3 patterns over multi-day period.

Table 4.5 shows socio-demographic descriptors of the homogenous groups with similar travel pattern. For example, males have more heterogeneous pattern than females either worker or non-worker. Generally, old people have a simple pattern than younger.

As automobile is more suited for chained trips, consequently, workers who has driver license, live in household with vehicles tend to repeat more than 4 patterns.

It can be seen from Table 4.5 that married people, family with small child have homogenous pattern than single. Moreover, suburb and inner-city residence tend to repeat more pattern than those in central area residence. This may be because, their work and activity locations tend to be farther from home locations, consequently, they tend to be more mobile.

In the following chapter, the differences in transition among representative between workers and non-workers are analyzed by Markov chain model.

Table 4.4 Homogenous Groups of Workers/ Non-Workers

		worker	non-worker	Group Number
	Combination of Representative Pattern	Frequency	Frequency	
1	who has only A pattern over 30 days	0	0	1
2	who has only B pattern over 30 days	0	0	
3	who has only C pattern over 30 days	2	6	
4	who has only D pattern over 30 days	0	0	
5	who has only E pattern over 30 days	0	0	
6	who has only AB pattern over 30 days	0	0	
7	who has only AC pattern over 30 days	0	2	
8	who has only AD pattern over 30 days	0	0	
9	who has AE pattern over 30 days	3	0	
10	who has BC pattern over 30 days	0	0	
11	who has BD pattern over 30 days	0	0	
12	who has BE pattern over 30 days	3	0	
13	who has CD pattern over 30 days	1	30	
14	who has CE pattern over 30 days	0	0	
15	who has DE pattern over 30 days	0	0	
	Total by Column (percent by column)	**9** (8.3%)	**38** (44.2%)	
16	who has ABC pattern over 30 days	0	1	2
17	who has ABD pattern over 30 days	1	0	
18	who has ABE pattern over 30 days	19	1	
19	who has ACD pattern over 30 days	1	18	
20	who has ADE pattern over 30 days	2	0	
21	who has ACE pattern over 30 days	1	0	
22	who has BCD pattern over 30 days	1	3	
23	who has BCE pattern over 30 days	0	0	
24	who has BDE pattern over 30 days	3	0	
25	who has CDE pattern over 30 days	1	4	
	Total by Column (percent by column)	**29** (26.6%)	**27**(31.4%)	
26	who has ABCD pattern over 30 days	1	1	3
27	who has ABCE pattern over 30 days	17	0	
28	who has ABDE pattern over 33 days	12	2	
29	who has ACDE pattern over 30 days	9	12	
30	who has BCDE pattern over 30 days	1	0	
	Total by Column (percent by column)	**40** (36.7%)	**15**(17.4%)	
31	who has ABCDE pattern over 30 days	31	6	4
	Total by Column (percent by column)	**31** (28.4%)	**6** (7.0%)	
	Total	**109** (100%)	**86** (100%)	

Table 4.5 Socio-Demographic Descriptors of Homogenous Groups

Worker

Socio-demographic measures		Group 1 N=9	Group 2 N=29	Group 3 N=40	Group 4 N=31
Male		0.67	0.66	0.68	0.71
Age	less than 24 years old	0	0.07	0.08	0.06
	25-34 years old	0.11	0.21	0.16	0.23
	35-44 years old	0.55	0.24	0.38	0.29
	45-54 years old	0.11	0.31	0.28	0.19
	55-64 years old	0.56	0.17	0.10	0.23
	over than 65 years old	0.11	0	0	0
Vehicles licence ownership		0.89	0.83	0.93	1
Married		1	0.62	0.68	0.67
Family with small child		0.67	0.24	0.25	0.32
Number of household member		3.67	2.57	2.73	2.67
Number of vehicles		1.33	1.28	1.47	1.39
Number of telecommunication connection		2.89	2.34	2.7	2.81
Household income [x1,000 DM]		5.01	4.31	4.96	4.76
Live in CBD		0.44	0.09	0.08	0.10
Live in Inner city area		0.22	0.25	0.28	0.22
Live in Suburb area		0.34	0.66	0.64	0.68

Non-worker

Socio-demographic measures		Group 1 N=38	Group 2 N=27	Group 3 N=15	Group 4 N=6
Male		0.4	0.4	0.27	1
Age	less than 24 years old	0	0.04	0.07	0.17
	25-34 years old	0.03	0.02	0.27	0.17
	35-44 years old	0.11	0.22	0.20	0
	45-54 years old	0.06	0.11	0	0.33
	55-64 years old	0.34	0.31	0.26	0.16
	over than 65 years old	0.46	0.30	0.20	0.17
Vehicles licence ownership		0.61	0.70	0.73	0.67
Married		0.74	0.67	0.4	0.5
Family with small child		0.09	0.15	0.33	0.17
Number of household member		2.23	2.26	2.13	2.17
Number of vehicles		1	1.07	1	0.83
Number of telecommunication connection		1.94	1.48	1.81	1.50
Household income [x1,000 DM]		3.78	3.46	3.41	2.87
Live in CBD		0	0	0.06	0.17
Live in Inner city area		0.40	0.30	0.27	0.33
Live in Suburb area		0.60	0.70	0.67	0.50

4.4 Summary

In describing multi-day travel patterns, daily travel patterns are classified into a set of five representative patterns which are interpretable and reflect many aspects of travel patterns. This is done by applying principal component analysis (PCA) in two steps, then applying *k*-mean cluster analysis.

The daily travel pattern of each individual on each day is characterized in this study by 29 descriptors and this study is concerned only with daily travel patterns observed on weekdays. The sample used in the analysis contains 8,506 daily patterns (or, person-days) observed in the six-week survey period. On average 26.83 daily patterns are available from a respondent.

The total of 15 components from original data sets are considered as significant components and used in the second step. The first six components from the second step collectively account for 78.2 percent of the total variance, and are used in the subsequent analysis. Based on the six components obtained from the PCA analysis, internally homogenous subgroups of daily travel patterns are identified with a *k*-means clustering algorithm. Five representative patterns are selected for further analysis.

Multi-day travel patterns are conceived as a sequence of these representative patterns, and relative frequencies of representative pattern examined. It has been shown that the occurrence of representative patterns varies substantially from individual to individual, and is quite different between workers and non-workers as well. The result also indicate that workers seem to repeat more than 3 patterns, which implies that workers have more heterogeneous pattern than non-workers. Although, non-workers have simple patterns tend to repeat less than 3 patterns over multi-day period.

The transitions among the patterns over a course of six weeks are analyzed with the framework of Markov chain models in Chapter 5.

In chapter 6, two state Markov chain model is applied to examine the occurrence and sojourn duration of representative pattern.

Chapter 5

Stochastic-Process Approach to Multi-Day Travel Behavior

···a stochastic process in which the future development depends only the present state, but not on the past history of the process or the manner in which the present state was reached (Feller,1968, p 444).

This chapter offer stochastic-process approach to analyze multi-day travel behavior. First, the recurrence structure of representative travel patterns over six-week period is analyzed by discrete-state Markov chain model. Transitions among the patterns over course of weeks examined. The expected amount of time (in the term of the number of discrete time point, or number of days in this case) after leaving a pattern until visiting another given pattern is represented in this study by stopping time concept. The power of transition matrix of daily travel pattern is examined by its limiting distribution. Second, the tendencies in succession of representative pattern and sojourn duration of daily travel pattern are then investigated by two-state Markov chain model. The variations in sojourn duration are then examined by regression model.

Next section offers a theoretical description of a discrete state Markov chain model as well as the concept of stopping time. It followed by section that presents the concept of limiting distribution of daily travel pattern. After that, the empirical results of Markov chain models are discussed

In following section, the description of two-state Markov chain model is presented and the examination of sojourn duration is described then. Summary is presented in the last part of this chapter.

5.1 Recurrence Structure of Multi-Day Travel Patterns

5.1.1 Discrete State Markov Chain Model

Suppose individual's daily travel behavior can be expressed as a stochastic process, i.e., a process comprising random events that place over time. An example is the number of shopping trips one has taken varies over time as his needs change from day to day.

Stochastic models may be classified on the basis of being "discrete" or "continues", depending on whether or not time variable is treated in these terms, or depending or not they process the Markov property. Markov process models process this property and can be regarded as generalizations of Markov chains; in a Markov process model a transition from one state to another state can take place at any point in time. i.e., time is continues, but in a Markov chain the state varies only at discrete time intervals.

There are several ways of characterizing such a stochastic process. For example, to measure the time elapsed between successive occurrences of changes and record the nature of respective occurrence. (e.g., the variation in shopping frequency); and another way is to observe the state of the process at discrete time points.

A discrete state Markovian model is useful in describing of the characteristics of dependence in a sequence of events. The process depicted by the model assumes one of N discrete states, which comprise the state space, $S = \{1, 2, \ldots, N\}$. The process comprises a series of visits to these states. Applications of Markovian models can be found in earlier studies of trip chaining. Kitamura (1988) applied a simple Markov chain model to describe day-to-day variations in shopping activity engagement.

In this study, we employ a discrete-time, Markov chain model whose state space is the set of five representative daily patterns, i.e., $S = \{A, B, C, D, E\}$.

The first-order history independence is assumed in the Markov chain model of this study, i.e., a state (or, a travel pattern in this case) occupied by the process at time $t + 1$ depends on the state occupied at time t, but is conditionally independent of the previous history of the process given the state at time t.

The transition from state to state is governed by transition probabilities, the p_{ij}. The transition probabilities can be generalized in the form of a transition matrix **P**. The elements of **P** denote the probability that the process occupies state j at time $t + 1$, given that process was in state i at time t:

$$p_{ij} = \Pr[X_{t+1} = j \mid X_t = i] \tag{5.1}$$

which indicates that the process is conditionally independent of the past history, $X_0, X_1, \ldots, X_{t-1}$, given X_t. In the current context, this implies that the probability that travel pattern j will be taken tomorrow, given that the pattern taken today is i, does not depend on the patterns that have been taken in the past.

The transition probabilities, which completely determine the Markov process, must satisfy the following properties:

$$p_{ij} \geq 0, i, j \in S \tag{5.2}$$

and

$$\sum_{j \in S} p_{ij} = 1 \tag{5.3}$$

where S is the state space as before. A consistent estimator of a transition probability is

$$p_{ij} = \frac{n_{ij}}{n_i} \tag{5.4}$$

where n_{ij} is the observed number of transitions from state i to state j and n_i is the number of transitions from state i to all other states. With the assumption of conditional history independence, the probability of being in some state, say j, at future time, $t + s$, can be deduced from the transition probabilities.

Since the elements of the matrix must be non-negative and the sum of the elements in any row is 1 (eq 5.3), each row called a probability vector and the matrix **P** is a stochastic matrix.

The expected amount of time in the term of the number of discrete point, or the number of days in this case) after leaving a state (hereafter called "initial state") until visiting another given state ("target state") is represented in this study by stopping time.

Letting the initial state be i, and j be the target state. Then stopping time from i to j is defined as the recursive relationship

$$t(i,j) = 1 + \sum_{k \neq j} p(i,k)t(k,j) \tag{5.5}$$

where
$t(i,j)$=the mean stopping time to j from the initial state i.

5.1.2 Limiting Distribution (Steady-State Vector) of Daily Travel Patterns

First order Markov chain model applied in Section 5.1 and considered two time period two adjacent time period t and $t+1$ and estimated transition probability p_{ij} from state i to j from time period t to time period $t+1$.

Let p^s_{ij} denote the elements of $\mathbf{P}^s$. The probability of moving from state i to state j after s transitions can be obtained by raising **P** to its sth power and taking its (i,j) elements.

When s approaches infinity and assuming **P** is aperiodic, $\mathbf{P}^s$ will converge to **P*** with all the rows equal to the vector of limiting probabilities. Let $\mathbf{\Pi}^T = (\pi_1, \pi_2, \ldots, \pi_k)$ denote vector of limiting probabilities where $\sum_j \pi_j = 1$.

After a long time, the initial state is forgotten and the initial state is forgotten and

$$\lim_{n \to \infty} p^n_{ij} = \pi_j \tag{5.6}$$

where, π_j is the limiting probability that is independent of the starting (initial) state i and it is the unique solution of the following system equations

$$\pi_j = \sum_{i=0}^{\infty} \pi_i p_{ij}$$

$$\sum_{j=0}^{\infty} \pi_j = 1 \tag{5.7}$$

Solving this system equations give us the vector of limiting probabilities or the steady-state vector when Markov chain reaches equilibrium. “Steady-state” means that if this distribution ever occurs, there will no further changes.

Limiting distribution is also the long-term distribution. No matter what the starting distribution, the long-term distribution approaches the steady state. Limiting probability of being in a state j after k transition is;

$$\frac{E[\text{visits to state j in n steps given start in state i}]}{\text{n}} = \frac{\sum_{k=1}^{n} P_{ij}^{k}}{n}$$

$$\lim_{n\to\infty} \frac{E[\text{visits to state j in n steps given start in state i}]}{n} = \lim_{n\to\infty} \frac{\sum_{k=1}^{n} P_{ij}^{k}}{n} = \pi_j \qquad (5.8)$$

where, P_{ij}^{k} is the probability of moving from state i to state j after k transition.

A critical issue in such applications is whether the observed behavioral process can be concerned as a Markov chain, and especially whether the assumption of history dependence and time homogeneity a valid. Empirical test of these assumptions are discussed by Anderson and Goodman, 1953).

5.1.3 EMPIRICAL RESULTS

Discrete State Markov Chain model

Using the Markovian framework, the characteristics of transitions among the five daily travel patterns are explored in this section. In this study, state-to-state transition probabilities are estimated for each individual based on the six-week trip diary data. Figure 5.1 shows sample distributions of individual-based transition probabilities for transitions from Pattern E to itself for workers and those from Pattern C to itself for non-workers.

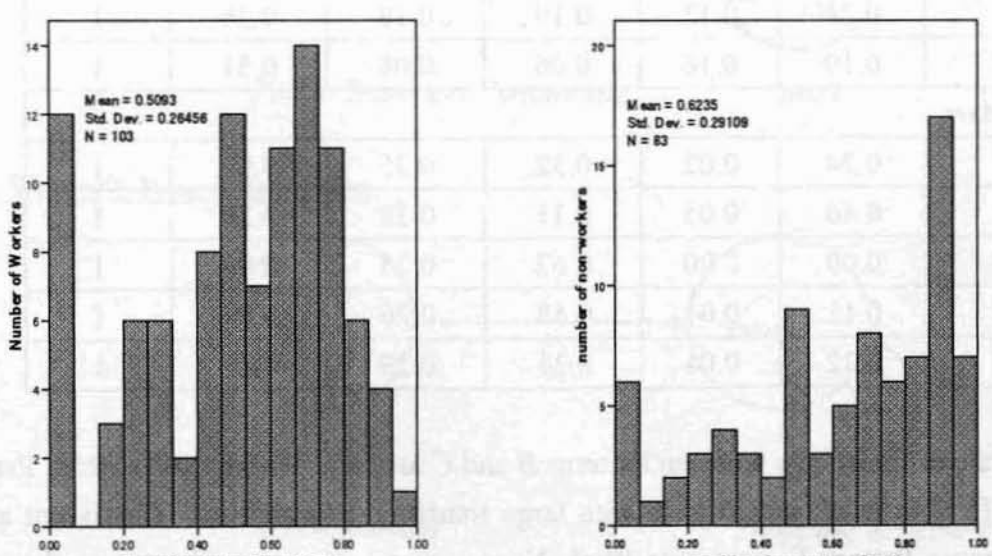


FIGURE 5.1 Sample Distributions of Individual-based Transition Probabilities

The frequency distributions make it evident that transition probabilities vary substantially from individual to individual. Individuals, either workers or non-workers, are by no means homogenous in terms of transition probabilities among daily travel patterns.

It can be seen from Figure 5.1 that, although workers have large transition probabilities from Pattern *E* (*Work*) to itself with a mean of 0.51, their values vary greatly across individuals. Likewise, non-workers' transition probabilities from Pattern *C Shopping & Leisure* to itself vary greatly. It is obvious that individuals are quite heterogeneous in terms of pattern-to-pattern transition probabilities.

We now turn to average transition probabilities obtained by pooling observations from workers and non-workers, respectively. Table 5.1 shows transition matrices (a transition matrix is a matrix of state-to-state transition probabilities) for workers and non-workers. The table indicates that transition probabilities from a pattern to itself are often large, particularly for non-workers, and indicate that some patterns tend to be persistent, particularly Pattern *E* for workers and Pattern *C* for non-workers as noted above.

TABLE 5.1 Transition Probabilities among Representative Daily Patterns

From	To "Pattern"					Total
"Pattern"	A	B	C	D	E	P
Workers						
A	0.21	0.1	0.07	0.09	0.53	1
B	0.21	0.2	0.05	0.08	0.46	1
C	0.17	0.07	0.28	0.18	0.30	1
D	0.24	0.13	0.19	0.18	0.26	1
E	0.19	0.16	0.06	0.08	0.51	1
Non-Workers						
A	0.24	0.02	0.32	0.35	0.07	1
B	0.46	0.05	0.11	0.18	0.20	1
C	0.09	0.00	0.62	0.25	0.04	1
D	0.11	0.01	0.58	0.26	0.04	1
E	0.22	0.01	0.31	0.29	0.17	1

For workers, direct transitions between Patterns *B* and *C* are rare. Workers move from Pattern *A* to Pattern *E*, *E* to itself, and *B* to *E* with large transition probabilities. This is not at all surprising because Pattern *E* represents *Work*. Non-workers' salient transitions, on the other hand, are: *C* to *C* (*Shopping & Leisure* to itself), *D* to *C* (*Accompanying* to *Shopping &*

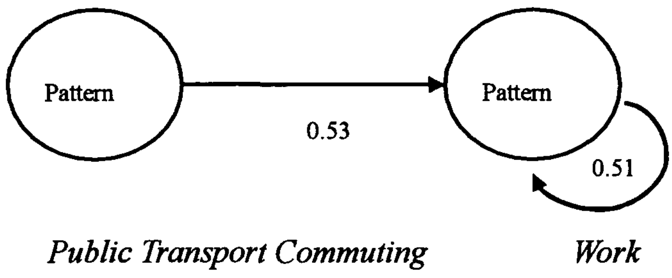
Leisure) and *B* to *A* (*Car–based Multiple Visits* to *Public Transport Commuting*). No transitions are observed from Pattern *C* to *B* (*Shopping & Leisure* to *Car–based Multiple Visits*) for non-workers, and Pattern *D* and Pattern *B* for non-workers have small transition probabilities as a destination state.

Differences in transition among representative pattern between workers and non-workers can be roughly observed by the number of individuals in each transition. Descriptive statistics of workers and non-worker are given in Table 5.2 As workers have obligation activities on weekday, large number of workers observed in transition between Pattern E (*Work*) to itself, Pattern A to E (*Public Transport Commuting- Work*) and Pattern B to E (*Car–based Multiple Visits-Work)* and small number of workers move from Pattern C to B (*Shopping & Leisure* to *Car–based Multiple Visits*); Pattern B to C.

Although, the large number of non-workers is observed in transition Pattern C to itself (*Shopping & Leisure);* Pattern c to D ((*Shopping & Leisure- Accompanying),* likewise, Pattern D to C. Non-workers less like to make switch to Pattern B *Car–based Multiple Visits.*

The mean transition probability among representative patterns ranges from 0.003 to 0.62 among individuals. Hereafter, the transitions that have transition probability greater than 0.50 values considered as "typical" transition.

Worker's Typical Transition



Non-Worker's Typical Transition

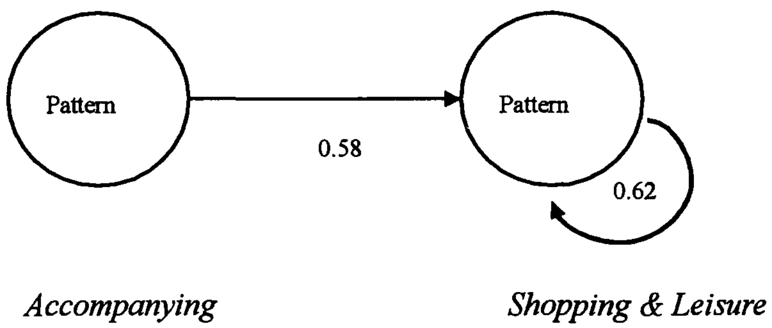


Figure 5.2 "*Typical*" Transitions among Representative Patterns

TABLE 5.3 Stopping Time among Representative Daily Patterns

		Worker					Non-Worker				
		To pattern									
		A	**B**	**C**	**D**	**E**	**A**	**B**	**C**	**D**	**E**
From pattern	**A**	0	7.79	13.6	11.0	2.13	0	175	2.52	3.34	21.6
	B	4.99	0	13.9	11.2	2.27	5.73	0	3.17	3.86	18.4
	C	5.21	8.21	0	9.72	2.83	9.77	179	0	3.79	22.6
	D	4.83	7.73	11.8	0	2.85	9.53	177	1.91	0	22.5
	E	5.10	7.33	13.8	11.1	0	8.26	177	2.58	3.56	0

Expected amount of time (in the term of the number of days) after leaving initial state until visiting another given state are estimated and presented in Table 5.2 It can been seen from Table 5.2 that workers tend to have longer stopping time to Pattern C (*Shopping & Leisure)* and Pattern D (*Accompanying)* from other given states and shorter stopping time from any initial states to Pattern E (*Work*). This implies that Pattern E is successively engaged after engaging in another pattern and tends to be recurrent for workers.

For non-workers, they have shorter time to Pattern C (*Shopping & Leisure)* and Pattern D (*Accompanying)* from other given initial states, which means that Pattern C and D to be recurrent for non-workers, dominantly engaged after leaving another patterns. On the other hand, non-workers have longer stopping time to Pattern E (*Work*) and relatively longer stopping time to Pattern B (*Car-based Multiple Visits)* from any given initial states. This is because, no transitions are observed from Pattern C to Pattern B for non-workers. Plus, the transition to Pattern B from other origin patterns was very small (see Table 5.1).

Limiting Distribution of Daily Travel Pattern

The distribution of limiting probability (steady-state vector) of representative pattern is shown in Figure 5.3 and in Table 5.4 for whole workers and non-workers. Many interesting finding is made from estimated limiting distribution of representative patterns. The most interesting finding is that there is no change in distribution of representative patterns over six-weeks which show that the initial distribution (observed distribution) of representative patterns not changed as time goes on.

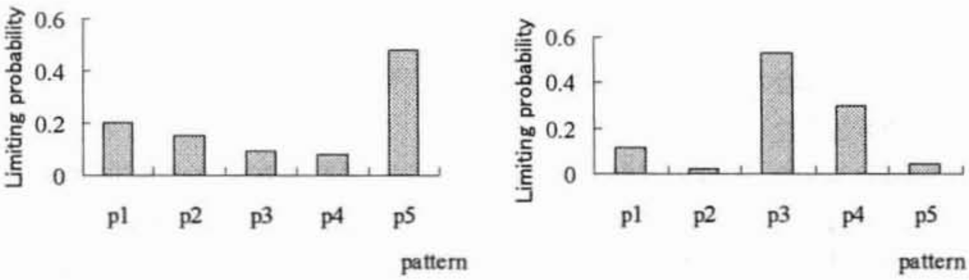


FIGURE 5.3 Limiting Distribution of Representative Patterns

TABLE 5.4 Limiting Distribution (Steady-State vector) of Representative patterns

	Pattern A *Public Transport Commuting*	**Pattern B** *Car-based Multiple Visits*	**Pattern C** *Shopping & Leisure*	**Pattern D** *Accompanying*	**Pattern E** *Work*
Workers	0.20	0.15	0.09	0.08	0.48
Non-Workers	0.11	0.02	0.53	0.30	0.04

We can see from Table 5.4 that for workers, Pattern E *Work* still dominant over time. Moreover the steady state vector for Pattern A *Public Transport Commuting* and Pattern B *Car-based Multiple Visits* are shows that Pattern A and B also prevalent over days.

Table 5.4 also give us, after long time (for example: after several days or weeks) non-workers tend to engage in Pattern C *Shopping & Leisure* and Pattern D *Accompanying* frequently. However, limiting probability for Pattern B *Car-based Multiple Visits* shows that non-workers hardly engage in Patterns B

We can also notice an interesting pattern here: Transition probabilities among representative patterns are given as:

Workers: **Non-Workers**

$$P = \begin{pmatrix} 0.21 & 0.10 & 0.07 & 0.09 & 0.53 \\ 0.21 & 0.20 & 0.05 & 0.08 & 0.46 \\ 0.17 & 0.07 & 0.28 & 0.18 & 0.30 \\ 0.24 & 0.13 & 0.19 & 0.18 & 0.26 \\ 0.19 & 0.16 & 0.06 & 0.08 & 0.51 \end{pmatrix} \qquad P = \begin{pmatrix} 0.24 & 0.02 & 0.32 & 0.35 & 0.07 \\ 0.46 & 0.05 & 0.11 & 0.18 & 0.2 \\ 0.09 & 0.003 & 0.62 & 0.25 & 0.04 \\ 0.11 & 0.01 & 0.58 & 0.26 & 0.04 \\ 0.22 & 0.01 & 0.31 & 0.29 & 0.17 \end{pmatrix}$$

and after five transition were have

$$P^5 = \begin{pmatrix} 0.200 & 0.142 & 0.095 & 0.101 & 0.461 \\ 0.200 & 0.142 & 0.095 & 0.101 & 0.461 \\ 0.200 & 0.142 & 0.095 & 0.101 & 0.461 \\ 0.200 & 0.142 & 0.095 & 0.101 & 0.461 \\ 0.200 & 0.142 & 0.095 & 0.101 & 0.461 \end{pmatrix} \quad P^5 = \begin{pmatrix} 0.124 & 0.008 & 0.554 & 0.268 & 0.052 \\ 0.125 & 0.008 & 0.552 & 0.268 & 0.052 \\ 0.124 & 0.008 & 0.557 & 0.269 & 0.052 \\ 0.124 & 0.008 & 0.556 & 0.268 & 0.052 \\ 0.124 & 0.008 & 0.554 & 0.268 & 0.052 \end{pmatrix}$$

Above matrices show that by the time we look at 5 transitions, no matter what starting pattern, the probability of being engaging in Pattern E(*Work*) is 0.46 for workers and the probability of pursue Pattern C (*Shopping& Leisure)* is 0.55. It shows that after several transitions, the rows of transition matrices are approaching the steady-state distribution vector.

It is assumed in this study that the limiting distribution of daily travel patterns will vary across individuals, e.g., everybody has different transition probability after long time passed. This assumption can be seen clearly from individual-based limiting probability (steady-state vector) of daily travel patterns. Figure 2 shows the distribution of limiting probability among individuals. The individuals who have the limiting probabilities of certain pattern are between 0 and 0.09 was excluded because it means that individuals not or hardly engaged in that pattern considered.

5.2 Occurrence and Sojourn Duration of Daily Travel Pattern

The Markov model in Section 5.1 describes the transition among the five travel patterns and thus the recurrent structure among them. In this section, we consider the case where we are interested in the occurrence of one particular pattern out of the five patterns and represent the set of states by two states: *success* and *failure*.

Two state Markov chain model is applied to examine the tendencies in succession of representative pattern and sojourn duration of daily travel pattern. The variations in sojourn duration are then examined by regression model.

5.2.1 Two-State Markov Model

An individual's travel pattern varies from day to day. It is viewed in this chapter that this variation is random, and each representative pattern occurs with certain probability. The approach taken in this study is to establish these probabilities.

The occurrence of one particular pattern out of the five patterns is represented as two states: *success* and *failure*. A success represents a visit at the state of interest (hereafter referred to as "*s*" state); a failure, or "*f*" state, represents a visit at one of the remaining states.

A graphical description of the transitions in the two-state Markov chain model is given in Figure 5.4.

There are four possible transitions for each representative pattern:

- *Failure (f)* – to- *Failure (f)*
- *Failure (f)*- to- *Success (s)*
- *Success (s)* –to- *Failure (f)*
- *Success (s)* to *Success (s)* and taking place with transition probabilities, p_{ff}, p_{fs}, p_{sf} and p_{ss}, respectively.

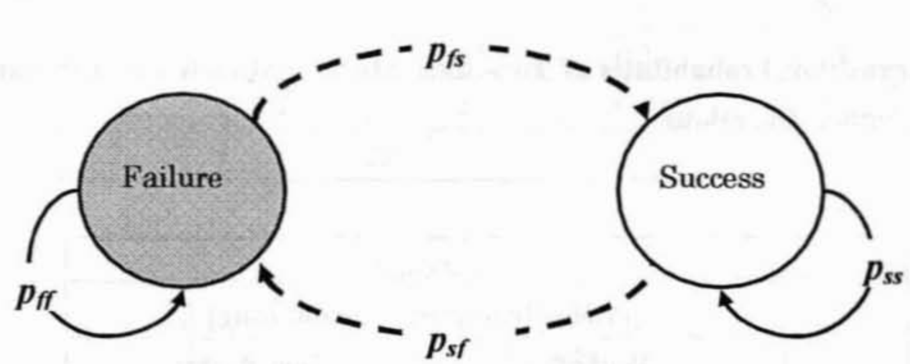


FIGURE 5.4 Graphical Representation of Two-State Markov Chain Model

Let W be a random variable which represents the number of successive days the process will remain in s state, given that the process is in state s currently. Then,

$$\begin{aligned}
&\Pr[W = n] \\
&\quad = \Pr[X_{m+1} = s, X_{m+2} = s, \ldots, X_{m+n-1} = s, X_{m+n} = f \mid X_m = s] \\
&\quad = \Pr[X_{m+1} = s \mid X_m = s]\Pr[X_{m+2} = s \mid X_{m+1} = s]\cdots \\
&\quad\ \Pr[X_{m+n-1} = s \mid X_{m+n-2} = s]\Pr[X_{m+n} = f \mid X_{m+n-1} = s] \\
&\quad = (1 - p_{sf})^{n-1} p_{sf}
\end{aligned}$$

where $p_{ss} = 1 - p_{sf}$.

The distribution of W is geometric with parameter p_{ss} and its mean is

$$E(W)=\sum_{n-1}^{\infty} n p_{ss}^{n-1} p_{sf} = \frac{1}{1-p_{ss}} = \frac{1}{p_{sf}} \tag{5.9}$$

W shall be called the *sojourn duration* in the state. The transition probabilities of this two-state model can be easily estimated for each of the five patterns and the mean sojourn duration can be obtained for each pattern using Eq. (5.9). Variations in sojourn duration are examined in the following section by applying regression model.

5.2.2 EMPIRICAL RESULTS

Table 5.5 presents the model estimation results for the propensity to engage in representative pattern (pattern occurrence) and the expected number of consecutive days in which the same travel pattern is pursued (mean sojourn duration).

TABLE 5.5 Transition Probabilities of Two-State Markov Models and Estimated Mean Sojourn Durations

	Pattern A [*Public Transport Commuting*]			
	Worker		Non-Worker	
	F	**S**	**F**	**S**
F	0.81	0.19	0.91	0.09
S	0.79	0.21	0.76	0.24
T_A	1.27		1.32	

	Pattern B [*Car-based Multiple Visits*]			
	Worker		Non-Worker	
	F	**S**	**F**	**S**
F	0.87	0.13	0.99	0.01
S	0.80	0.20	0.95	0.05
T_A	1.25		1.05	

	Pattern C [*Shopping & Leisure*]			
	Worker		Non-Worker	
	F	**S**	**F**	**S**
F	0.91	0.09	0.44	0.56
S	0.72	0.28	0.37	0.63
T_A	1.39		2.70	

	Pattern D [*Accompanying*]			
	Worker		Non-Worker	
	F	**S**	**F**	**S**
F	0.92	0.08	0.75	0.25
S	0.82	0.18	0.73	0.23
T_A	1.22		1.37	

	Pattern E [*Work*]			
	Worker		Non-Worker	
	F	**S**	**F**	**S**
F	0.57	0.42	0.96	0.04
S	0.48	0.52	0.81	0.19
T_A	2.08		1.23	

The important results from the pattern occurrence and mean sojourn duration analysis are as follows:

- Transitions from *S (success)* to *S (success)*, *F (failure)* to *S (success)* are large for Pattern *C*, particularly for non-workers. It implies that those non-workers who pursue Pattern C (*Shopping& Leisure*) tend to pursue day after day successively, i.e., Pattern *C* tend to occur over a multi-day period among those non-workers who pursue it at all. Non-workers' mean sojourn duration in Pattern *C* is 2.78 days.

- Pattern C is positively history dependent for non-worker, i. e the probability of engaging in a *Shopping and Leisure* activity is larger if the same type of pattern has been engaged in the past or probability of returning to Pattern C after completing the another pattern.

- Although, Pattern C *Shopping and Leisure* have found to be negatively history dependent for worker, i.e if workers less likely to pursue *Shopping& Leisure* activity if they engaged in shopping past.

- Pattern *E Work,* on the other hand, most likely to be the highly recurrent in a worker's daily travel pattern. , with mean sojourn duration of 2.08 days. This is logical, Pattern *E* is worker's s obligatory pattern.

- Two-state Markov chain model reveals that non-workers who pursue Pattern B (*Car-based Multiple Visits*) less likely to pursue day after day successively, Result indicate that transitions from *S (success)* to S *(success)* is lower; transition *S (success)* to *F (failure)* to are large.

5.2.3 Analysis of Sojourn Duration of Daily Travel Pattern

The mean sojourn duration in each representative pattern is examined in this section by applying regression model (SPSS 13.0 is used). The unit of analysis is the individual here, and expected sojourn duration estimated for each individual using p_{sf} as in Eq. (5.9) is the dependent variable of the analysis.

The general form of the model is

$$Y_i = \beta' X_i + \varepsilon_i \tag{5.10}$$

where Yi is the dependent variable, β is the vector of coefficients, Xi is the vector of explanatory variables, ε_i is the random error term, and i refers to the individual.

Obviously only those cases for which an enough number of sojourns is available from the individual to estimate psf can be included in the regression analysis. Consequently, regression models are developed for Patterns C, E and A for workers and Patterns C and D for non-workers. Table 5.6 provides variable definitions and their sample statistics.

Table 5.7 presents the results of regression model. An inspection of the means and standard deviations of the dependent variables would indicate that expected sojourn durations in the respective patterns vary substantially across the sample individuals. Both workers and non-workers are heterogeneous in terms of the recurrence structure of travel patterns.

TABLE 5.7 Models of Sojourn Durations

Dependent Variable	Workers						Non-workers			
	T_C		T_E		T_A		T_C		T_D	
	coeff	t-ratio	coeff	t-ratio	coeff	t-ratio	coeff	t-ratio	coeff	t-ratio
Constant	6.01	5.05	3.53	1.82	2.66	2.9	5.4	1.12	1.43	2.01
Male [D]	0.43	0.98	0.39	0.49	0.42	1.0	0.87	0.72	-0.94	-0.53
Married [D]	0.59	1.12	-0.04	-0.04	-0.41	-0.76	-1.58	-1.09	0.16	0.79
Driver's License Holding [D]	-2.70	-2.79	-0.50	-0.35	-1.45	-2.03	-1.66	-1.18	-0.10	-0.51
- 24 years old [D]	0.004	0.01	-0.70	-0.43	-0.43	-0.96	-7.17	-2.05	0.72	1.46
25 - 34 years old [D]	0.44	0.13	-0.40	-0.42	-0.43	-0.73	-4.78	-1.90	1.09	3.39
35 - 44 years old [D]	-0.83	-0.19	0.70	0.44	0.42	0.73	-0.02	-0.01	-0.12	-0.41
45 - 54 years old [D]	-0.21	-0.063	1.47	1.49	0.17	0.32	-1.6	-0.69	0.21	0.53
55 - 64 years old [D]	0.52	0.94	2.08	1.72	0.02	0.03	-1.01	-0.81	0.39	2.13
Household with small children [D]	-0.78	-0.01	0.07	0.06	-0.48	-0.87	-4.47	-1.70	0.73	1.99
Number of household members	0.11	0.32	0.28	0.48	0.11	0.38	2.03	1.71	-0.32	-2.10
Number of motor vehicles	0.13	0.37	0.23	0.38	0.21	0.65	-0.29	-0.27	-0.22	-1.41
Number of telecomm. connections	-0.16	-1.27	-0.10	-0.42	-0.10	-0.79	0.22	0.45	-0.15	-0.21
Household income [x1000DM]	-0.21	-1.89	-0.37	-1.81	-0.02	-0.24	0.29	0.55	0.07	1.03
CBD [D]	1.32	1.90	3.59	2.43	0.13	0.16	-1.02	-0.19	-0.31	-0.39
Inner city [D]	-1.49	-2.23	0.06	0.07	-0.05	-0.12	-0.17	-0.04	0.40	0.62
Suburbs [D]	-0.34	-0.78	-0.07	-0.07	0.05	0.10	-1.35	-0.31	0.58	0.92
Number of observations	60		102		96		77		76	
Mean dependent variable value	1.81		3.21		1.63		3.60		1.55	
SD of dependent variable	0.51		0.78		0.37		1.12		0.26	
R^2	0.14		0.14		0.11		0.21		0.35	
F	1.66		0.85		0.75		1.10		1.88	

TABLE 5.6 Variable definitions and their sample statistics

Variable	Definition	Mean	SD
Individual Socio-Demographics			
Male [D]	1 when individual is male	0.59	0.49
Married [D]	1 when individual is married	0.69	0.47
Driver's License Holding. [D]	1 when individual holds a driver's license	0.83	0.38
- 24 years old [D]	1 when individual is less than 24 years old	0.16	0.23
25 - 34 years old [D]	1 when individual is from 25 to 34 years old	0.17	0.35
35 - 44 years old [D]	1 when individual is from 35 to 44 years old	0.25	0.44
45 - 54 years old [D]	1 when individual is from 45 to 45 years old	0.19	0.38
55 - 64 years old [D]	1 when individual is from 55 to 64 years old	0.23	0.42
Household Socio-Demographics			
Household with small children [D]	1 when there are children less than 6 years old in household	0.23	0.42
Number of household members	Number of members in household	2.53	1.06
Number of motor vehicles	Number of cars available to household	1.24	0.72
Number of telecommunications connections	Number of telecommunications connections in household	2.27	1.69
Household income	Household income [x1000DM]	4.25	1.85
Residential Area			
CBD [D]	1 when individual's household located in CBD area	0.07	0.25
Inner city [D]	1 when individual's household located in inner city area	0.30	0.46
Suburbs [D]	1 when individual's household located in suburb area	0.63	0.48

[D]: A 0-1 dummy variable as defined.

Only a few explanatory variables are significant for both workers and non-workers, partly because the sample size is small. At the same time, it may be the case that heterogeneity in sojourn duration may be difficult to explain with the types of explanatory variables typically used in travel behavior analysis. Quite interestingly, household characteristics are mostly not significant in any of the models. The effects of selected variables are discussed below.

Workers who live in CBD area tend to have longer sojourn durations, and those with higher household incomes shorter sojourn durations, in Pattern C Shopping & Leisure and Pattern E Work.

It may be the case that workers in central city tend to have less variable travel patterns while higher income workers tend to be more variable. Having a driver's license tends to make workers' sojourns in Pattern C and Pattern A Public Transport Commuting shorter. Shorter sojourn durations in A are intuitively agreeable as a driver would have the option to commute to work by car. It may also be conjectured that a worker with a driver's license tends to be more mobile and tends to have more variable travel patterns and hence shorter sojourn durations.

5.3 SUMMARY

Using continuous six-week travel diary data from Karlsruhe and Halle, Germany, this chapter has examined the multi-day travel behavior by applying stochastic-process approach. Only travel patterns on weekdays have been examined in this study; travel patterns on weekend days remain as a subject of future research.

Multi-day travel patterns are conceived as a sequence of these representative patterns, and transitions among the patterns over a course of six weeks are analyzed with the framework of Markov chain models. The results have provided several insights into the variability of daily travel patterns and interconnection between different daily patterns. For example, transitions from a daily pattern to itself are often frequent, particularly among non-workers, and some daily patterns tend to be persistent with successive engagement over a large number of days.

Heterogeneity in multi-day travel behavior is represented in this study as the variation in pattern-to-pattern transition probabilities and stopping time both tabulated at the individual level. It has been shown that individuals, either workers or non-workers, are heterogeneous in terms of multi-day travel behavior; their pattern-to-pattern transition probabilities vary substantially across individuals. The study also reveals higher level of heterogeneity in stopping time, i.e., the expected number of days until engaging in a target pattern after engaging in a given initial pattern. The results of this chapter show that individuals have more than one typical transition in daily travel pattern.

The power of transition matrix of daily travel pattern is examined by its limiting distribution. The result in this analysis show that that there is no change in distribution of representative patterns over six-weeks which show that the initial distribution (observed distribution) of representative patterns not changed as time goes on. However, the individuals are no homogeneous in the term of multi-day travel pattern. The limiting distributions of representative patterns quite vary from individual to individual.

This chapter also has examined the occurrence and sojourn duration of daily travel pattern by two-state Markov model. The results of two-state Markov chain model reveal the differences in the tendencies in succession across representative patterns. Some patterns tend to be positively history dependent; i. e the probability of engaging in particular pattern is larger if the same type of pattern has been engaged in the past.

Expected sojourn durations in travel patterns is estimated for each individual and implies that

individuals are also heterogeneous in term of mean sojourn duration in a pattern (i.e., the expected number of successive days pursuing the pattern).
Systematic heterogeneity is examined through regression analysis of expected sojourn duration in each representative pattern. Empirical results indicate, for example, having a driver's license tends to contribute to a higher level of day-to-day variability in travel patterns. It is also shown that variability in daily travel is highly dependent on the individual's residence location; an individual living in central area is more likely to regularly pursue travel patterns with shopping and leisure activities, for example.

Chapter 7 should examine the characteristics of history dependence in the transition between daily travel patterns, and reexamine the presence of heterogeneity in light of history dependence.

Chapter 6

Who Has a Homogenous Pattern? Who Does Not?

Who has a homogenous pattern over days and who does not? This question has examined in this chapter. Next section offers a brief description of homogeneity in daily travel pattern and formulates the hypotheses examined in this study. The concept of homogeneity index of daily travel pattern and its distribution is described in the following section. The empirical results of models are presented then. Finally, a brief conclusion of this study is provided.

6.1 How homogenous is travel?

How homogenous is travel? This question has been investigated for many years. There are number of reasons for explicitly recognizing homogeneity of daily travel patterns. First, understanding the homogeneity of engagement patterns across different types of activities is important in understanding the nature of day-to-day variability in individuals' travel behavior patterns.

There is a ground for expecting homogeneity in daily travel pattern. The idea that individuals establish relatively homogenous, fixed travel patterns has been a convenient, compelling and widely adopted simplifying assumption among transportation researchers (Adler and Ben-Akiva 1979; Golledge 1970). They have simply assumed that most travel (particularly weekday travel) is stable, routine, stereotyped and habitual (Jones 1979; Hensher 1976).

Huff and Hanson, in their serial papers (Hanson & Huff, 1982, 1986, 1988; Huff and Hanson, 1986, 1990), have shown that certain specific attributes of an individual's activity-travel pattern (such as the mode one taken, depart time for work) may be routine and repetitive.

Moreover, Cullen (1978) argued that the homogeneity of daily travel behavior is to be expected because it is one way for a person to cope with complexity and variety of the urban environment.

Kasturirangan et al.(2002) showed that there is a relatively high degree of consistency in activity engagement from day to day. When a person engages in a certain activity on a one day, the person appears to be likely to repeat the activity the next day compared with a person who did not perform that activity on the first day. Similarly, when a person does not to engage in a certain activity on one day, then the person is more likely not to engage in that activity the next day too.

Focused to shopping activity engagement, Kitamura (1988a) found that those who engaged in shopping in the past tend to engage in shopping again in the future, and those who forewent shopping tend to forego in future also.

Pas (1987) noted that behavior is repetitious, but the level of repetition is different for different travel behavior/socio-demographic groups and that the types of behaviors that are most repetitious differ for each group. In a related study, Pas and Koppelman (1987) showed that individuals with more constraints in their activity-travel patterns have less intrapersonal variability.

The brief review above highlights the presence of homogeneity in activity-travel patterns. However, almost all of studies have addressed particular trip purposes or activity patterns. Filling this gap, the present study seeks to analyze a daily pattern as a whole and examine the homogeneity of daily travel patterns.

Moreover, the analysis of homogeneity index is critical to quantifying intrapersonal variability and contributes to the body of knowledge on multi-day travel behavior.

6.2 The Hypotheses of the Homogeneity of Daily Travel Pattern

There are several hypotheses that are conceivable in examining the homogeneity in travel pattern over multi-day period.

- The homogeneity of daily travel patterns highly depends on an individual's daily routine as well as their work/residence locations.
- Individuals who live and work in CBD area have more regular life styles; they might have more homogenous travel pattern than other types of area residents.
- Having a driver's license more likely to have automobile and tend to have more day to day variations in travel pattern. Because the automobile is more suited for chained trips, consequently their travel patterns tend to be heterogeneous.
- As non-workers, the homogeneity of daily travel pattern will depend on their life cycle. Young people up to 24 years old, tend to engage in more activities jointly such as sports or clubs, their travel pattern will be less homogenous from day to day.
- Moreover, non-workers between 25-35 years old will have unstable travel patterns, because they may be in the child-bearing stage and would pursue different activities as their household needs.
- It can also be assumed that a larger household increases the degree of homogeneity of travel patterns due to the reduction in intra-household task allocation.

6.3 The homogeneity index of daily travel patterns

The homogeneity of travel patterns over a multi-day period is represented in this study by the "*homogeneity index*" concept. Using the fraction of representative patterns *A, B, C, D* and *E*, the homogeneity index *H* of person *i* over six-week period can be presented as

$$H^i = (P_A^i)^2 + (P_B^i)^2 + (P_C^i)^2 + (P_D^i)^2 + (P_E^i)^2 \tag{6.1}$$

where H^i is the homogeneity index of person i , P_A^i, P_B^i, P_C^i, P_D^i and P_E^i are fraction of representative patterns *A,B,C,D* and *E*. If H^i takes value on the maximum value of 1.0, then it indicates that the travel patterns of individual over longer period are completely homogenous which means repeating a certain pattern day after day and when H^i takes the minimum value of $5x(1/5)^2=1/5$, then travel patterns of individual over longer period are most heterogeneous.

The distribution of homogeneity index of travel patterns is presented for whole workers and non-workers in Figure 6.1. The values of homogeneity index substantially vary among individual for both workers and non-workers. Figure 6.1 show that non-workers have larger mean value of H^i than workers. It seems that non-worker's pattern more homogenous than workers.

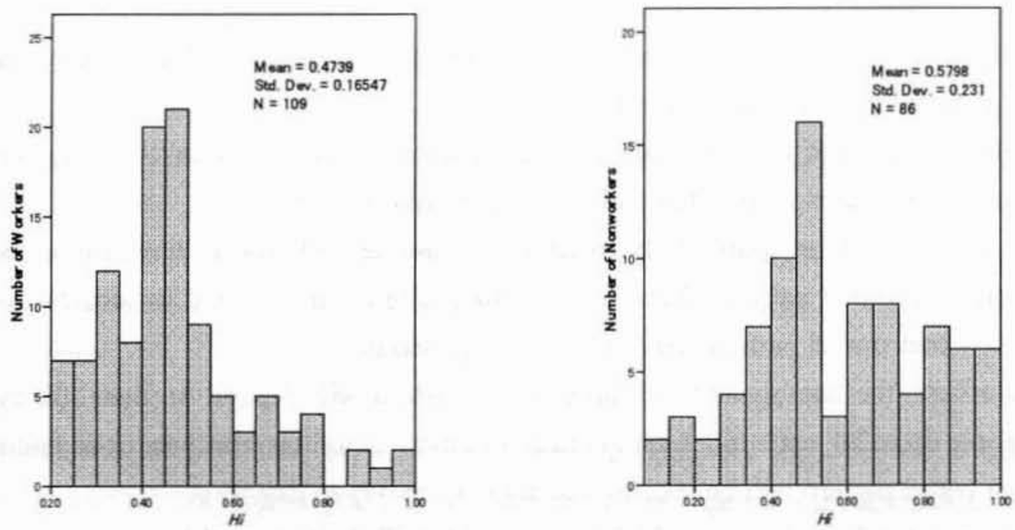


Figure 6.1 Distribution of Homogeneity Index

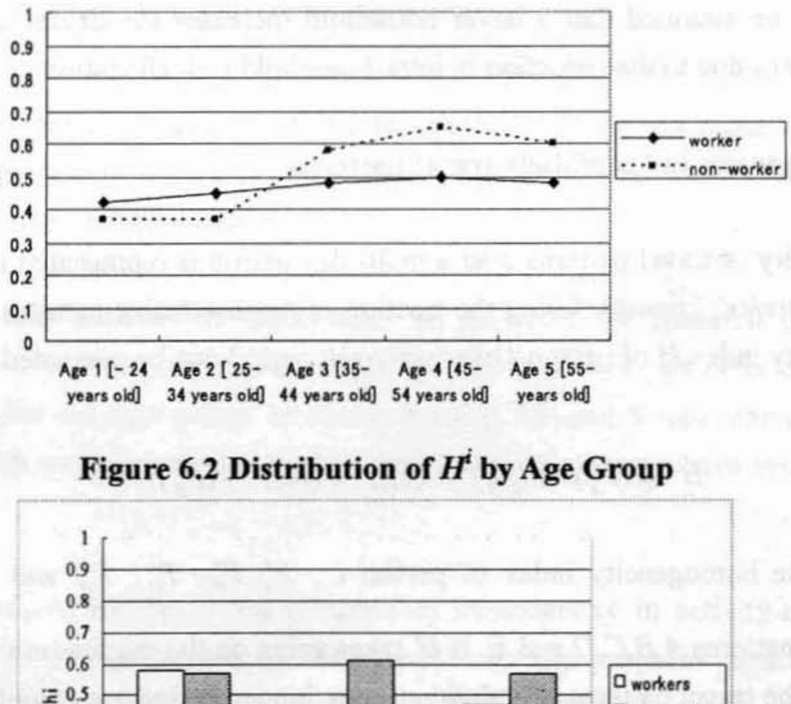


Figure 6.2 Distribution of H^i by Age Group

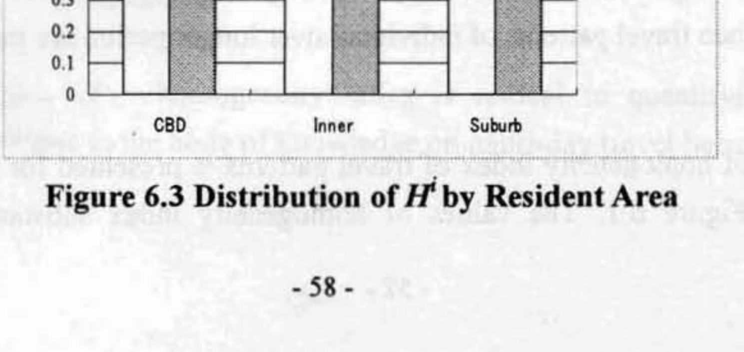


Figure 6.3 Distribution of H^i by Resident Area

Figure 6.2 and 6.3 present the distribution of H^i index by age and resident area type respectively. Residence area is classified into three: central business district (CBD), inner city and suburb. Differences in homogeneity index value between workers and non-workers more clearly described.

Interesting finding is that homogeneity index value substantially varies across age groups, specifically, among non-workers.

As workers, tend to have obligatory activities on weekdays, their travel pattern are relatively homogenous, particularly those aged over 35 years old.

For non-workers, H^i values quite vary among age groups. It can be seen from Figure 6.2 that non-workers engage in more activities jointly such as sports or clubs. Consequently, H^i takes on smaller value. However, non-workers over than 35 years old have relatively homogenous patterns.

Figure 6.3 show that CBD workers have more homogenous pattern than other residence area type workers. Inner city workers tend to have smaller value of H^i. This is may be because the inner city area, which lies between CBD and suburb, has more mixed opportunities for various activities, encouraging the residents to be more mobile.

As non-workers, do not have obligatory trips, they have relatively homogenous pattern, especially, inner-city and suburb residents.

The homogeneity index of daily travel pattern is further examined by ordinary least square (OLS) regression model. The models are estimated with LIMDEP Version 8.0 by Econometric Software,Inc. The general form of the model is,

$$H^i = \beta' X^i + \varepsilon_i \qquad i=1,2,\dots\dots\dots N, \qquad (6.2)$$

where, H^i is dependent variable- homogeneity index, i refers to individual, β is the vector of coefficients, X^i is the vector of explanatory variables, ε_i is the random error term. Results of estimation are given in Table 6.1. Salient results are summarized as follows:

For workers, driver license is found to have significant effects on homogeneity index of daily travel pattern. As drive's license reduce the stability of daily travel pattern. It shows that holding driver's license makes their travel pattern more heterogeneous.

Table 6.1 Models of Homogeneity Index

Dependent Variable-H_i	Workers		Non-workers	
	coeff	t-ratio	coeff	t-ratio
Constant	0.65	9.78	0.56	6.47
Driver's License Holding [D]	-0.18	-3.08		
-24 years old [D]			-0.38	-2.41
25-34 years old [D]			-0.33	-3.21
35-44 years old [D]				
45-54 years old [D]				
55-64 years old [D]				
Family with small child [D]			-0.19	-1.60
Number of household members			0.07	1.72
Number of mot.vehicles				
Number of connections	-0.01	-1.22		
Household Income [x1000DM]		-		
CBD [D]	0.14	2.69		
Inner city area [D]				
Suburb [D]				
Number of observation	109		86	
Mean of dependent variable value	0.48		0.59	
SD of dependent variable	0.17		0.11	
R^2	0.15		0.21	
F	3.54		2.21	

Another interesting finding is, the H^i values of worker are positively influenced by residence area type, worker who live in CBD area tend to be more homogenous daily travel pattern.
It implies that if workers residing and working in central city tend to have more regular lifestyles.

It also appears that if the ease in communicating with others or acquiring information encourages workers to engage more activities, consequently their travel patterns tend to be less homogenous.

For non-workers, age was found to be significant explanatory variable that have predominant influences on H^i. The results show that young non-workers have negatively effect on homogeneity index; this is understandable, young people engage in more activities jointly such as sports or clubs and their travel pattern tend to be more unstable.

On the other hand, the presence of small child negatively contributes to H^i .The number of household members positively influences on H^i. This may be result of intra-household task allocation, with more household members, fewer household tasks are assigned to each member consequently their travel pattern tend to be more homogenous.

6.4 Summary

This chapter has proposed a framework for analysis of multi-day travel patterns. The focus has been on homogeneity index of daily travel patterns, and how the values of homogeneity index vary from individual to individual.

The homogeneity in daily travel pattern is represented in this study as homogeneity index of daily travel pattern. Variation in homogeneity index is examined then. Homogeneity index is determined based on the fraction of representative patterns which obtained from classification analysis in Chapter 4.

The results of this chapter consistent with findings of previous chapters and indicate that either workers and non-workers are heterogeneity in the term multi-day travel ; the values of homogeneity index substantially vary individual to individual, across different age groups as well as.

The findings of empirical analysis thus support the hypothesis of the study on homogeneity in daily travel pattern. As non-workers do not have obligatory trips and activity, their pattern tends to be more homogeneous from day to day. However, it also have shown that homogeneity index vary greatly across non-worker's age groups. Young people engage in more activities jointly such as sports or clubs and their travel pattern tend to be less homogenous.

The study also reveals that, having a driver's license, resident area types tend to contribute to a higher level of day-to-day variability in travel patterns. The results provide several insights into quantifying intrapersonal variability and contribute to the body of knowledge on multi-day travel behavior.

Chapter 7

Analysis of Heterogeneity in Daily Travel Pattern Variation

Heterogeneity is defined as individual differences in *"unmeasured variables"* and explained that *"previous experience may appear to be a determinant of future experience solely because it is a proxy for temporally persistent unobservable"* (Heckman, 1981,pp. 91-92).

This chapter reexamines the unobserved heterogeneity in daily travel pattern variation across individual. Mixed logit models (MXL) have been widely adopted for this purpose, which allows randomly distributed preferences of attributes across individuals, is employed to accommodate the random heterogeneity across individuals and to cope with the correlation between repeated choices.

Next section offers the brief overview about the heterogeneity among individual. After that, the description of Mixed logit model is presented. The results of empirical analysis are discussed then. The chapter is concluded with a summary of finding.

7.1 Introduction

Similar individuals facing the same set of choices often make different choices. Explaining this phenomenon has long interested economists and other social scientists. One explanation is that so-called similar individuals are quite heterogeneous in that they have differing unobservable tastes in spite of the fact that their observable characteristics are the same. Another explanation is that these individuals do have the same basic tastes but have heterogeneous past experiences, and these experiences shape their assessment of future choices. Although a combination of both explanations may situation, these two approaches to individual behavior have very different econometric modeling implications.

In the study of individuals travel behavior, it is crucial to capture the heterogeneity among in individual's taste. These differences can be characterized by systematic and random heterogeneity. The systematic heterogeneity is identified by some observed individuals characteristics, whereas the random heterogeneity comes from some unobserved individual factors. Capture these factors in travel behavior, however, could not be done without longitudinal data. Repeated observation of the same respondents make it possible to analyze history dependence in daily travel pattern, unobserved contribution factors are well controlled. On the other hand, the use of longitudinal data allows us to address the issue of unobserved individual heterogeneity in daily travel pattern.

The present study uses the mixed logit model to test the heterogeneity in travel pattern variation, the analysis focus on how patterns of day-to day variation are different across individuals? How people different in the term of multi-day travel pattern?

The model form of mixed logit termed as variable coefficient model (Ben-Akiva and Lerman, 1985), has been applied in a number of studies such as travel model choice analysis, shopping location choice analysis and econometric demand modeling (Algers et al, 1998; Bhat, 1998; Bhat ,1999; Revelt and Train, 1998). It generalizes the standard logit by allowing the coefficients of observed variables to vary randomly over individuals rather than being fixed.

7.2 Model Specification

The utility that indivual *n* obtains from alternative *j* in choice situation *t* is

$$U_{njt} = \beta_n^{'} x_{njt} + \varepsilon_{njt} \tag{7.1}$$

where, x_{njt} is vector of observed variables, coefficient vector βn is observed for each *n* and varies in the population with density $f(\beta_n \mid \theta^*)$ where θ^* are (true) parameters of this distribution, and ε_{njt} is an unobserved random terms that is distributed iid extreme value, independent of β_n and x_{njt}. Conditional on β_n , the probability that person n chooses alternative i in period t is standard logit:

$$L_{nit}(\beta_n) = \frac{e^{\beta_n' x_{nit}}}{\sum_j e^{\beta_n' x_{njt}}} \tag{7.2}$$

The unconditional probability is the integral of the conditional probability over all possible values of βn, which depends on the parameters of the distribution of βn,:

$$Q_{nit}(\theta^*) = \int L_{nit}(\beta_n) f(\beta_n \mid \theta^*) d\beta_n \tag{7.3}$$

For maximum likelihood estimation we need the probability for each sampled individual's sequence of observed choices.

Let $i(n,t)$ denote the alternative that individual n chose in period t. Conditional on βn, the probability of individual n's observed sequence choice is the product of standard logit[1]:

$$S_n(\beta_n) = \prod_t L_{ni(n,t)t}(\beta_n) \tag{7.4}$$

Unconditional probability for the sequence of choices is

$$P_n(\theta^*) = \int S_n(\beta_n) f(\beta_n \mid \theta^*) d\beta_n \tag{7.5}$$

There are two concepts of parameters in this description. The coefficient vector βn, is the parameters associated with person n, representing that person's tastes. These tastes vary over people; the density of this distribution has parameters θ^* representing, for example mean and covariance of βn . The goal is to estimate θ^*, that is the population parameters that describe the distribution of individual parameters.

Parameters are estimated by maximize the simulated log-likelihood function. In particular, $P_n(\theta)$ is approximated by a summation over randomly chosen values βn. For a given value of the parameters θ, a value of βn is drawn from its distribution. Using this draw of βn, $S_n(\beta_n)$ -the product of standard logist –is calculated. This process is repeated for many draws, and the average of resulting $S_n(\beta_n)$'s is taken as approximate choice probability:

$$SP_n(\theta) = (1/R) \sum_{r=1,\ldots,R} S_n(\beta_n^{r|\theta}) \tag{7.6}$$

[1] This specification assumes that the individual's tastes, as represented by β_n are the same for all choice situations. The model can be generalized to allow the coefficients vector to vary over t as well as n. Our data consists of repeated choices within survey, such the assumption of β_n constant over seems reasonable.

Where R is the number of repetitions (i.e., draw of βn), $(\beta_n^{r|\theta})$ is the r-th draw from $f(\beta_n|\theta)$, and $SP_n(\theta)$ is the simulated probability of individual n' s sequence of choice. The estimation software used is NLOGIT 3.0 by Econometric Software.

As noted in Chapter 5, the heterogeneity in multi-day travel behavior is represented in this study as the variation in pattern-to-pattern transition probabilities is tabulated at the individual level. The results show that either workers or non-workers are heterogeneous in terms of multi-day travel behavior; their pattern-to-pattern transition probabilities vary substantially across individuals. Particularly, the workers are quite heterogeneous tend to have large transition probabilities from *Pattern E (Work).* Non-workers' transition probabilities from *Pattern C* (*Shopping & Leisure*) to itself vary across individuals. Consequently, mixed logit models are developed for *Patterns E* for workers and *Patterns C* for non-workers to analyze the unobserved heterogeneity in respective patterns. All of empirical results in this study are produced using LIMDEP 8.0, Econometric Software, Inc.

7.3 The Empirical Results

The sample used in the Pattern E (Work) model comprises 3061 daily patterns (or person days) of 109 workers, while the Pattern C (Shopping& Leisure) model comprises 2146 daily patterns of 86 non-workers. These daily patterns are observed in the six-week survey periods.

The number of alternatives j in equation (7.1) is two for both models.
Pattern E (*Work*) -work; other
Pattern C (*Shopping & Leisure*) –shopping& leisure participation and other.

The several types of variables enter as elements of x in equation (7.1). They include individual socio-demographic characteristics, household characteristics, and residential area type. The results of estimation are shown in Table 7.1.

The log-likelihood at convergence of the joint Pattern E (*Work*) system is -1992.9.Among individual socio-demographic variables sex and driver license holding have a positive effect on choice of working activities. There are indications that that man more likely to participate in working activity compared to women. Having a driver's license more likely to have automobile and encourage worker to engage working activity.

Several variables associated with household socio-demographics affect the decision to participate in working activity participation. The variables married and number of household members positively contributes to working decision. Again, as expected, workers who live in CBD area tend to engage working activity.

Table 7.1 The Results of Model Estimation

Variable	Model 1 Pattern E (*Work*)		Model 2 Pattern C (*Shopping & Leisure*)	
	coef	t-stat	coef	t-stat
Constants				
Work	-1.11	-5.99	-	-
Shopping & Leisure	-		1.09	3.24
Male [D]	0.47	4.84	-0.35	-2.72
Married [D]	0.38	3.51	0.37	2.68
Driver's License Holding [D]	0.39	2.52	-0.35	-2.09
- 24 years old [D]	-	-	-	-
25 - 34 years old [D]	-	-	0.35	2.65
35 - 44 years old [D]	-	-	-	-
45 - 54 years old [D]		-	-	-
55 - 64 years old [D]	-0.19	-1.07	-	-
Family with small child [D]	-0.14	-1.21	-0.92	-3.44
Number of household members	0.20	3.69	0.03	4.55
Household Income [x1000DM]	-	-	-0,24	4.54
CBD [D]	0.47	3.27	-	-
Inner city area [D]	-	-	-	-
Suburb area [D]	-	-	-0.48	-1.84
Karlsruhe [D]	-0.093	-1.04		
Number of observation	3061		2146	
Log-likelihood	-1992.9		-1287.9	

The results of model Pattern C (*Shopping & Leisure*) also shown in Table 7.1. Household characteristics Among the individual socio-demographic variables, gender and age was the variables that statistically significantly effect on choice of shopping & leisure activity engagement. The first individual socio-demographic variable in table is a male dummy variable. The results indicate that women more like to do shopping& leisure trips compared to men. This possibly reflect that the continuing trend to shoulder a major part of household maintenance responsibilities.

The result also indicates that non-workers with age between 25-34 years old are more likely to engage in shopping & leisure activity than other.

A household with a large member of non-working persons are more likely to engage shopping& leisure activities. As household income increases, as expected, non-worker seems to participate in shopping& leisure activity frequently. Household income has significantly effect on decision to join shopping and leisure activities.

Non-workers who reside in suburb area are less likely to make shopping & leisure trips compared to other area residents. This may be because suburb area, which located farther and not easy access to stores in dense area.

7.4 Unobserved Heterogeneity in Characteristics of Pattern E (*Work*)

The focus of this section is on examining the heterogeneity in attributes of *Pattern E (Work).* The attributes characterizing the *Pattern E* include:

a. number of work trip made by workers
b. time expenditure for work activity.

The sample of current analysis comprises 2,597 working frequency, which is the number of working trips over six-week period, extracted from 109 full workers, who worked at least 35 hours per week. The recorded number of work trips ranges from 1 to 6 trips per day and time expenditure for work ranges 14 to 1015 (min) per day. The average number of work trip 1.23 trips and average time expenditure for work is 503.91 (in min) per day. The results of estimation are shown in Table 7.2 and Table 7.3.

Among individual socio-demographic variables sex and driver license holding have a positive effect on number of work trips. There are indications that that man more likely to do work trips compared to women. Having a driver's license more likely to have automobile and encourage worker to make more work trips.

However, the number of work trips is negatively influenced by the number of household members and by the number of vehicles in household. This may be result intra-household task allocation. On the other hand, the presence of small children in household positively contributes to work trips.

The result also indicates those workers who live in household with telecommunications connections more likely to make trips for work activity. The ease in communicating with other and acquiring information always encourage worker to work.

Workers who live in CBD area tend to make more work trips. An interesting result is number of work trips significantly influenced by the day of week. On Tuesday, workers more likely to make work trips compared other days of week.

Table 7.3 shows the results of time expenditure for work activity model. The consistent with finding of number of work trip model, man are more likely to need an extended duration of

Table 7.2 Models of Number of Work Trips

	Coef	t-ratio
Constant	1.18	17.44
Male [D]	0.08	3.03
25-34 years old [D]	-0.29	-6.65
35-44 years old [D]	0.04	1.17
45-54 years old [D]	-0.04	-1.36
55-64 years old [D]	-	-
Married [D]	-0.02	-0.88
Driver license holding [D]	0.17	3.85
Number of household member	-0.01	-0.65
Number of vehicle in household	0.06	-5.97
Number of telecommunications connections	0.28	3.78
Family with dependent children [D]	0.16	4.51
Household Income[x1000 DM]	0.004	0.58
CBD [D]	0.19	3.93
Inner [D]	0.02	0.71
Tuesday[D]	0.08	2.34
Wednesday[D]	0.02	0.60
Thursday [D]	-0.007	-0.22
Friday[D]	-0.07	-1.88
Number of observation	2597	
Mean of dependent variable	1.23	
SD of dependent variable	0.59	
R^2	0.08	
Degree of Freedom	(17, 2579)	
F	12.97	
Log-L	-2330.3	

work activity than women. Furthermore, increasing the age, individuals are like to work for shorter period of time.

Worker's time expenditure for work activities highly influence by drive license. Workers who having a driver's license and car are spending short time than transit or non-motorized commuters.

Among the household characteristics, the presence of small children in household reduces expenditure time for work activity. On the other hand, lower household income increases the propensity to work for longer durations. The result also indicates that workers live in CBD area is less likely spends more time on working.

Table 7.3 Models of Time Expenditure for Work Activity

	Coef	t-ratio
Constant	525.9	40.6
Male [D]	69.4	11.7
25-34 years old [D]	-2.78	-0.22
35-44 years old [D]	8.54	0.95
45-54 years old [D]	16.6	2.36
55-64 years old [D]	-38.2	-4.83
Married [D]	-9.27	-1.30
Driver license holding [D]	-31.8	-3.39
Number of household member	-7.34	-1.63
Number of vehicle in household	14.3	6.60
Number of telecommunications connections	-0.61	-0.39
Family with dependent children [D]	-39.4	-5.17
Household Income[x1000 DM]	-5.71	-3.94
CBD [D]	-21.8	-2.15
Inner [D]	7.53	1.19
Karlsruhe [D]	2.58	0.46
Number of observation	2581	
Mean of dependent variable	530.91	
SD of dependent variable	125.5	
R^2	0.12	
Degree of Freedom	(15, 2567)	
F	24.39	
Log-L	-15962.37	

7.5 Unobserved Heterogeneity in Characteristics of Pattern C (*Shopping & Leisure*)

Differences in shopping & leisure behavior across individuals can be roughly observed by the number of shopping trips and time expenditure for shopping& leisure activity. The estimation results of models are shown in Table 7.4 and Table 7.5.

Table 7.4 presents the results of the number of shopping & leisure trips models. Gender and age was the variables that statistically significantly effect on number of shopping & leisure trips. The first individual socio-demographic variable in table is a male dummy variable. The results indicate that women more like to do shopping& leisure trips compared to men. This possibly reflect that the continuing trend to shoulder a major part of household maintenance responsibilities.

The result also indicates that increasing age, non-workers more likely to engage in shopping & leisure activity than younger.

A household with a large member of non-working persons are less likely to make shopping& leisure trips. However, household income increases, as expected, non-worker seems to do shopping& leisure trips frequently. Household income has significantly effect in number shopping & leisure trips.

Non-workers who reside in suburb area are less likely to make shopping & leisure trips compared to other area residents. This may be because suburb area, which located farther and not easy access to stores in dense area.

The result also indicate that individual live in Karlsruhe are more like engage in shopping and leisure activities than Halle city's residents. This is understable, the Karlsruhe city is the second largest city in Germany and center for shopping and cultural events. Day of week is variables that has predominant influences on shopping & leisure trips. Non-workers are more likely to do shopping and leisure trips on Wednesday among weekdays.

The results of time expenditure for shopping& leisure activities models are shown in Table 7.5 Driver license holding have a negatively effect on time expenditure for shopping& leisure activities. An individual who has drive license is less likely spends longer duration on shopping and leisure activities. Older individuals are more likely to engage in recreational activity for longer period of time.

The location variables, on the other hand, suggest that individual residing in inner city area seems to spend short duration on shopping and leisure activities. Day of week variable does not have significantly effect on time expenditure on shopping and leisure activities. Although, individuals more likely spend more time for discretionary on Thursday among weekdays.

Table 7.4 Models of Number of Shopping & Leisure Trips

	Coef	t-ratio
Constant	1.56	8.27
Male [D]	0.25	4.75
- 24 years old [D]	-0.22	-0.96
25-34 years old [D]	0.32	3.15
35-44 years old [D]	0.33	3.90
45-54 years old [D]	0.06	0.71
55-64 years old [D]	0.18	3.18
Married [D]	-0.11	-1.89
Driver license holding [D]	-0.23	-3.41
Number of household member	-0.20	-4.02
Number of vehicle in household	0.02	1.02
Number of telecommunications connections	-0.03	-1.61
Family with dependent children [D]	0.14	1.42
Household Income[x1000 DM]	0.10	4.53
CBD [D]	-0.22	-1.06
Inner [D]	-0.34	-1.98
Suburb[D]	-0.39	-2.34
Karlsruhe [D]	0.18	3.53
Tuesday[D]	0.12	1.83
Wednesday [D]	0.16	2.51
Thursday [D]	0.13	2.16
Friday [D]	0.14	2.27
Number of observation	1300	
Mean of dependent variable	1.34	
SD of dependent variable	0.74	
R^2	0.08	
Degree of Freedom	(21, 1278)	
F	5.26	
Log-L	-1404.38	

Table 7.5 Models of Time Expenditure for Shopping& Leisure Activities

	t_{shop}	
	Coef	t-ratio
Constant	67.43	8.39
Male [D]	3.09	0.72
- 24 years old [D]	-2.49	-0.14
25-34 years old [D]	14.32	1.73
35-44 years old [D]	-11.14	-1.63
45-54 years old [D]	-5.61	-0.80
55-64 years old [D]	21.42	4.73
Married [D]	0.77	0.77
Driver license holding [D]	-20.08	-3.65
Number of household member	0.74	0.18
Number of vehicle in household	6.89	3.70
Number of telecommunications connections	-1.09	-1.16
Family with dependent children [D]	2.91	0.37
Household Income[x1000 DM]	-1.87	-1.05
CBD [D]	-12.67	-1.21
Inner [D]	-10.03	-2.33
Suburb[D]	-4.13	-0.80
Karlsruhe [D]	-8.49	-2.11
Tuesday[D]	-4.12	-0.79
Wednesday [D]	4.37	0.85
Thursday [D]	10.08	3.20
Friday [D]	7.86	0.11
Number of observation	1299	
Mean of dependent variable	70.31	
SD of dependent variable	60.10	
R^2	0.08	
Degree of Freedom	(20, 1278)	
F	6.10	
Log-L	-7102.25	

Chapter 8

Conclusion

Using continuous six-week travel diary data from Karlsruhe and Halle, Germany, this study has developed the framework for the analysis of multi-day travel patterns. The focus has been on the recurrence of daily travel patterns as a whole over a long span of time, and how it varies from individual to individual.

This study examined how the daily travel as whole caries, how repetitious is travel and how patterns of-day-to-day variation is different across individual. Analyzing the characteristics of multi-day travel behavior as a stochastic process, then, examining recurrence structure of daily travel patterns over a course of days, moreover, quantifying patterns of day-to day variation at individual level, are unique and important contribution of this study as well.

Grouping of Multi-Day Travel Pattern

With the intent of treating daily travel as a whole, yet in a manageable manner, principal component analysis (PCA) and k-mean cluster analysis are applied to the six-week diary data to identify a small number of travel pattern classes which each contain observed daily patterns of similar characteristics.

The daily travel pattern of each individual on each day is characterized in this study by 29 descriptors and this study is concerned only with daily travel patterns observed on weekdays. The sample used in the analysis contains 8,506 daily patterns (or, person-days) observed in the six-week survey period. On average 26.83 daily patterns are available from a respondent.

The total of 15 components from original data sets are considered as significant components and used in the second step. The first six components from the second step collectively account for 78.2 percent of the total variance, and are used in the subsequent analysis. Based on the six components obtained from the PCA analysis, internally homogenous subgroups of daily travel patterns are identified with a *k*-means clustering algorithm. Five representative patterns are selected for further analysis.

Multi-day travel patterns are conceived as a sequence of these representative patterns, and relative frequencies of representative pattern examined. It has been shown that the occurrence of representative patterns varies substantially from individual to individual, and is quite different between workers and non-workers as well. The result also indicate that workers seem to repeat more than 3 patterns, which implies that workers have more heterogeneous pattern than non-workers. Although, non-workers have simple patterns tend to repeat less than 3 patterns over multi-day period.

The results show that daily travel patterns may be grouped into a small set of classes while retaining much of the information in the original travel patterns. In following section we summarize the finding of discrete-state Markov chain model in which the five patterns identified here, are represented as discrete states.

Stochastic-Process Approach to Multi-Day Travel Behavior

Using continuous six-week travel diary data from Karlsruhe and Halle, Germany, this chapter has examined the multi-day travel behavior by applying stochastic-process approach. Only travel patterns on weekdays have been examined in this study.

Multi-day travel patterns are conceived as a sequence of these representative patterns, and transitions among the patterns over a course of six weeks are analyzed with the framework of Markov chain models. The results have provided several insights into the variability of daily travel patterns and interconnection between different daily patterns. For example, transitions from a daily pattern to itself are often frequent, particularly among non-workers, and some daily patterns tend to be persistent with successive engagement over a large number of days.

Heterogeneity in multi-day travel behavior is represented in this study as the variation in pattern-to-pattern transition probabilities and stopping time both tabulated at the individual level. It has been shown that individuals, either workers or non-workers, are heterogeneous in terms of multi-day travel behavior; their pattern-to-pattern transition probabilities vary substantially across individuals. The study also reveals higher level of heterogeneity in stopping time, i.e., the expected number of days until engaging in a target pattern after engaging in a given initial pattern. The results of this study show that individuals have more than one typical transition in daily travel pattern. The power of transition matrix of daily travel pattern is examined by its limiting distribution. The result in this analysis show that that there is no change in distribution of representative patterns over six-weeks which show that the initial distribution (observed distribution) of representative patterns not changed as time goes on. However, the individuals are no homogeneous in the term of multi-day travel pattern. The limiting distributions of representative patterns quite vary from individual to individual.

This study also has examined the occurrence and sojourn duration of daily travel pattern by two-state Markov model. The results of two-state Markov chain model reveal the differences in the tendencies in succession across representative patterns. Some patterns tend to be positively history dependent; i. e the probability of engaging in particular pattern is larger if the same type of pattern has been engaged in the past.

Expected sojourn durations in travel patterns is estimated for each individual and implies that individuals are also heterogeneous in term of mean sojourn duration in a pattern (i.e., the expected number of successive days pursuing the pattern). Systematic heterogeneity is examined through regression analysis of expected sojourn duration in each representative pattern. Empirical results indicate, for example, having a driver's license tends to contribute to a higher level of day-to-day variability in travel patterns. It is also shown that variability in daily travel is highly dependent on the individual's residence location; an individual living in central area is more likely to regularly pursue travel patterns with shopping and leisure activities, for example. The empirical results from the study have important implications for transportation policy analysis and travel modeling and sheds new light on understanding daily travel pattern.

How Has a Homogenous Travel Pattern and Who Does Not?

The homogeneity in daily travel pattern is represented in this study as homogeneity index of daily travel pattern. Variation in homogeneity index is examined then. Homogeneity index is determined based on the fraction of representative patterns which obtained from classification analysis.

The results of homogeneity analysis consistent with findings of previous analysis and indicate that either workers and non-workers are heterogeneity in the term multi-day travel ; the values of homogeneity index substantially vary individual to individual, across different age groups as well as.

The findings of empirical analysis thus support the hypothesis of the study on homogeneity in daily travel pattern. As non-workers do not have obligatory trips and activity, their pattern tends to be more homogeneous from day to day. However, it also have shown that homogeneity index vary greatly across non-worker's age groups. Young people engage in more activities jointly such as sports or clubs and their travel pattern tend to be less homogenous.

The study also reveals that, having a driver's license, resident area types tend to contribute to a higher level of day-to-day variability in travel patterns. The results provide several insights into quantifying intrapersonal variability and contribute to the body of knowledge on multi-day travel behavior.

General Conclusion

This study has proved that the multi-day data is necessary to examine the variation in individual travel pattern and it make possible to examine the stochastic nature of daily travel pattern. Examination of variability in individual travel pattern in the spectrum from perfectly repetitious to purely random, is crucial for better understanding of daily travel behavior, but also to better development and evaluation of planning measures. In closing, I would like to emphasize that the empirical results from the study have important implications for transportation policy analysis and travel modeling. Ignoring the variability in individual travel pattern can lead to an overly optimistic picture of the effectiveness of transportation control measures. Moreover, an understanding of daily rhythms of individuals can inform land use planning by helping to match the supply of activity centers with demand for such centers.

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APPENDIX A:
Contents of The *Mobidrive* Main Survey Forms
(source: Axhausen et al., 2002)

TABLE A.1 Contents of the Household Questionnaire

Item	Coding and Comments
Number of residents	(Excluding family members who only visit occasionally)
Number of family members residing elsewhere	
Number of dogs	
Composition of vehicle fleet	Number of cars, bicycles, motorized cycles, small motorcycles, motorcycles, trucks, other (please specify)
Household membership in a car sharing organization	Yes, no
Permission to use vehicles of other households and frequency of use	Yes, no; about daily, more then once a week, once a week, twice or trice a month, once a month, less than once a month
Private parking space in a garage	Number, for up to three: (below building, below building elsewhere, garage on the lot, garage elsewhere); distance [m or min], monthly rent or purchase price
Other private parking spaces	Number, for up to three: type (yard, driveway, marked space, covered space, on public right-of-way); distance [m or min], monthly rent or purchase price
Distance to the closest bus stop	[m or min]
Distance to the closest tram stop	[m or min]
Distance to the closest heavy rail station	[m or min]
Size of accommodation	[m^2]
Type of accommodation	Apartment (in building of 7 or more), apartment (in building of up to 6), free standing single family home, duplex, terrace, flat within single family home
Ownership status	Owned, rented
Type of subsidy for accommodation	None, company housing, subsidized housing
Year of construction of accommodation	
Year of move	
Costs (rent of mortgage)	[DM] (excluding service charges, heating, electricity etc.)
Additional costs of housing	[DM]
Presence of	One balcony, multiple balconies, terrace, terrace, rooftop terrace, basement, attic, laundry room, drying room, garden, other (please specify)
Size of garden	[m^2]
Telecommunication resources	Number of land lines, mobile phones, fax machines, private email addresses, work-related email addresses
Monthly household income net after taxes and social security payments	- 1000, 1000 – 1799, 1800 – 2499, 2500 – 2999, 3000 – 3999, 4000 – 4999, 5000 – 7499, 7500 DM and more

TABLE A.2 Contents of the Person Questionnaire

Item	Coding and Comments
Given name	Abbreviations were possible
Sex	Female, male
Relation to other household members	Spouse/partner, parent, child, other (please specify)
Currently married	Yes, no
Types of education completed	None, primary school, minimum required years of schooling, intermediate exam, subject limited baccalaureate, baccalaureate, East German baccalaureate, apprenticeship, craft master, 3 year degree, university degree (sciences/engineering or other), other (please specify)
Status	Pupil, student, homemaker, part time employed, full time employed, self employed, in retirement, supporting family member, unemployed
Number of employers	
Number of work locations	
Number of working hours	[/week]
Address of work location	Street address of most frequently visited work location
Duration of employment	Starting years with different employers
Profession	Open
In education/further education	Yes, no
Number of qualification sought	
Number of hours in education	[/week]
Name and addresses of schools	
Presence of fixed time commitments	Yes, no
Type of fixed commitments	Clubs, civic, political, charitable, self improvement, care of family or friends, other (please specify) (tick all which apply)
Number of fixed commitments	[/week]
Number of hours spent on those	[/week]
Day of week and location of those	
License ownership	Yes, no
Type of licenses	Motorized bicycle, small motorcycle, motorcycle, car, truck, coach
Ownership of heavy rail discount card	Yes, no
Ownership of heavy rail season ticket	Yes, no and type (open) and area of validity
Ownership of local public transport season ticket	Yes, no and type (monthly, academic term, senior, pupil, other (please specify)) and area of validity
Nationality	German, other (please specify)

TABLE A.3 Contents of the Vehicle Questionnaire

Item	Coding and Comments
Type of vehicle	Bicycle, motorized bicycle, small motorcycle, motorcycle, car, truck, other (Please specify
Producer	Open (motor vehicles only)
Year of production	(motor vehicles only)
Year of purchase	(motor vehicles only)
Power	[PS] (motor vehicles only)
Motor size	[ccm] (motor vehicles only)
Type of fuel	Gasoline, diesel, other (please specify) (motor vehicles only)
Current odometer reading	[km] (motor vehicles only)
Type of bicycle	Mountain bike, racing bike, city bike, children's bike, other (bicycles only)
Age of bicycle	Less than two years, more than two years (bicycles only)
Mileage with the vehicle during the last twelve months	[km]
Owner of the vehicle	Personal (name, if household member); employer (name of the household member employed); other (please specify)
Main user of the vehicle	Name of household member
Other users	Names of household members
Most frequently used parking space	Yard, driveway, marked space, curb, garage, covered parking space, bicycle shed, basement, other (please specify)
Distance from parking space to home	[m or min]

APPENDIX B:

Table B1. Sequences of Representative Patterns over 6 Week: Worker (1)

1	Pattern A	Public Transport Commuting
2	Pattern B	Car Based Multiple Visits
3	Pattern C	Shopping& Leisure
4	Pattern D	Accompanying
5	Pattern E	Work

No	Individual ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	sum
1	1000091	2	2	2	2	2	5	2	2	4	1	4	3	4	4	4	4	4	4	4	4	4	1	1	4	4	1	4				**27**
2	1000481	5	5	5	5	5	2	1	5	5	5	2	2	2	5	5	5	5	5	5	2	1	2	2	1	2	2	5				**27**
3	1000521	2	2	2	2	5	2	5	5	5	5	5	5	5	5	4	5	3	5	5	5	5	5	5	5	5	5	2	5	1	5	**30**
4	1000531	2	5	5	5	5	3	3	5	5	2	5	2	2	5	2	5		5	3	5	5	5	5	5	5	5	2	5	1	5	**30**
5	1000761	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	5	2	2	5	1	2	2	2	2	1	2	2	2	5	5	**30**
6	1000851	5	5	5	5	2	2	5	5	5	2	5	5	5	1	5	5	5	5	5	2	5	5	2	2	3	5	3	1	5	5	**30**
7	1000852	3	3	3	3	4	4	1	5	1	1	5	5	1	3	4	1	5	5	1	4	2	3	3								**23**
8	1001041	5	5	1	5	5	1	5	1	5	5	5	5	1	5	5	5	1	5	1	1	5	1	1	1	5	5	1	2	2	5	**30**
9	1001042	1	1	1	5	1	5	1	5	1	5	1	5	5	5	1	5	5	1	5	5	5	1	1	5	5	1	1	3	2	1	**30**
10	1001051	5	5	5	5	5	5	5	5	5	5	5	5	1	5	1	5	1	1	5	1	1	5	1	1	1	1	2	1	1	1	**30**
11	1001053	1	1	1	2	1	5	5	5	1	2	1	5	1	5	5	5	5	5	5	2	5	5	5	5	4	1	5	1	5	1	**30**
12	1001172	5	5	5	5	3	3	3	4	1	5	5	5	5	5	5	5	1	2	2	5	1	5	2	1	2						**25**
13	1001452	1	5	5	5	5	5	5	5	5	5	1	1	5	5	1	1	1	5	5	2	5	5	5	5	5	1	1	1	5	5	**30**
14	1001472	4	5	2	2	5	5	2	5	2	2	2	2	2	2	2	1	2	2	5	2	5	2	2	2	5	2	3				**27**
15	1001541	5	5	5	2	5	5	5	5	2	5	5	5	5	2	4	5	5	5	2	5	5	5	2								**23**
16	1001592	2	5	5	2	2	5	5	2	1	2	5	5	2	2	5	2	5	1	5	2	5	5	5	5	2	5	5	2	2	5	**30**
17	1001832	2	4	3	1	4	3	3	3	3	3	4	1	3	3	1	3	3	3	1	4	3	1	5								**23**
18	1001891	5	1	1	2	2	2	1	5	3	5	5	1	4	1	5	5	2	5	5	5	2	5	5	5	2	5	5	5	5	5	**30**
19	1001892	5	5	2	1	5	2	5	1	5	5	2	5	5	5	5	1	3	1	1	5	5	1	5	1	1	5	5	1	2	1	**30**
20	1001893	5	5	5	2	2	5	2	1	5	1	1	2	5	5	5	5	1	5	2	5	2	5	5	5	5	1	5	5	2	1	**30**
21	1001941	1	5	5	2	5	5	1	5	2	5	5	5	5	2	5	5	1	5	5	2	5	5	2	5	2	1	5	2			**28**
22	1001961	5	5	2	5	5	5	2	5	2	2	5	2	2	2	4	5	2	5	5	2	1	1	5	2	2	2	2	5	1	5	**30**
23	1002291	5	5	2	2	2	2	1	2	2	2	2	1	5	5	2	2	2	5	1	5	2	2	2	1	2	5	2	5			**28**
24	1002311	2	2	2	2	5	5	5	2	2	2	2	2	5	2	2	2	4	2	2	2	2	2	2	2	5	2	2	1	1	1	**30**
25	1002901	5	1	5	1	5	5	5	3	5	5	5	5	1	1	1	1	5	2	5	2	2	5	5	2	5	5	2	2	5	1	**30**
26	1002931	2	5	1	1	5	1	5	1	1	5	1	5	5	5	2	5	2	1	1	1	5	5	5	5	5	1	2	1	5	4	**30**

27	1003091	1	5	5	5	5	5	2	2	2	5	2	2	2	2	2	2	1	2	2	2	5	5	5	2	5	3	5	5	5	2	30
28	1003201	2	2	1	5	5	5	2	5	5	5	5	5	5	5	5	5	5	5	2	2	5	2	5	5	1						25
29	1003351	5	2	5	5	1	5	5	5	1	5	5	2	5	5	5	5	5	1	1	5	5	5	5	2	5	5	5	4	2	3	30
30	1003411	3	3	5	2	5	4	4	4	5	4	2	3	5	3	3	5	4	4	1	1	1	4	4	5	5	4					26
31	1003412	3	1	2	4	5	3	3	5	4	3	3	1	3	1	3	3	3	1	4	1	5	1	1	3	3						25
32	1003493	5	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	30
33	1003501	1	5	4	1	5	3	4	1	4	4	1	1	4	1	4	5	5	5	1	2	5	5	2	5	4	1	1	2	4	1	30
34	1003521	2	5	2	5	2	2	2	5	2	5	1	5	5	2	5	5	5	5	2	1	5	5	5	5	5	5	1	5			28
35	1010331	5	5	5	2	1	5	5	2	5	5	5	5	1	3	5	5	5	5	5	5	1	1	5	5	1	5	5	5	5	5	30
36	1010561	4	4	5	4	4	1	1	4	1	2	5	5	5	5	1	1	1	5	1	4	5	1	5	5	1	5	5	5	5	5	30
37	1011351	1	5	5	2	2	2	5	5	2	1	1	5	1	5	5	2	5	5	1	5	1	2	3								23
38	1011721	2	5	5	2	5	5	2	2	2	2	5	2	2	2	2	2	2	2	5	2	4	2	2	5	5	5	5	5	4		29
39	1012001	2	2	5	5	5	5	5	5	5	5	5	1	5	5	5	5	5	5	1	4	2	5	1	5	5	2	2	2	4		29
40	1012202	1	1	2	5	1	3	1	4	3	2	1	5	3	1	1	4	1	4	4	1	1	4	2	5	1						25
41	1012231	1	5	5	2	5	5	5	5	5	5	5	5	2	2	5	5	2	5	2	5	5	5	2	1	5	5	4	5	1		29
42	1012552	5	5	5	1	1	5	1	5	1	4	5	1	5	5	1	5	1	4	5	5	4	5	5	5	5	5	5	5	1	4	30
43	1012972	5	5	5	1	5	2	5	1	5	5	5	1	5	1	1	5	5	2	3	3	3	5	2	5							24
44	1013201	5	5	5	5	5	5	5	2	1	5	5	3	1	5	5	1	3	5	5	5	1	1	5	5	1	5	5	4	5		29
45	1013261	3	3	4	1	5	5	5	5	4	5	2	1	2	1	3	5	5	5	5	5	2	5	5	5							24
46	1013351	5	5	5	5	2	1	5	5	5	1	5	5	5	5	1	5	5	5	5	5	4	5	4	4	5	3	1	5	5		29
47	1013381	5	5	5	5	5	5	5	5	3	5	5	5	2	2	5	5	5	5	5	1	1	5	5	1	5	5	5	5			28
48	1013391	3	3	5	2	1	5	2	1	2	4	4	2	1	1	2	1	5	2	1	5	1	3	5	2	1	5	5				27
49	1013393	5	5	5	2	2	2	5	1	1	2	1	3	1	1	5	5	1	1	1	5	1	5	2	1	1	1	2	5	2		29
50	2000061	1	1	5	5	4	3	3	3	3	1	1	1	1	1	3	1	4	3	3	3	3	3	3	3	1						25
51	2000171	5	5	2	5	5	5	2	3	5	2	2	5	2	2	1	5	5	5	5	1	5	2	2	5	1	5	5	5	2	2	30
52	2000181	5	5	5	5	5	5	5	5	5	5	1	5	5	5	2	1	5	5	5	5	1	5	5	5	5	5	5	5	5	1	30
53	2000191	1	5	5	5	2	5	5	2	1	5	2	1	2	2	3	4	3	3	3	2	1	2	1	1	2	1	2	5	1		29
54	2000212	5	1	5	5	5	2	5	5	5	5	2	5	5	4	5	5	2	5	2	4	5	2	5	5	5	2	5				27
55	2000221	4	4	4	1	3	1	1	3	1	1	1	1	3	1	1	1	3	4	5	5	3	3	3								23
56	2000281	2	2	2	2	2	2	5	2	5	2	2	2	5	5	5	5	2	2	5	5	5	2	2	2	2	2	5	5	4	5	30
57	2000482	1	5	5	5	5	2	5	5	1	1	5	5	5	1	5	5	2	5	2	5	5	1	5	5	1	5	5	5	5	5	30
58	2000501	1	1	4	5	3	4	5	1	1	3	5	5	4	5	3	4	4	1	4	4	5	5	1	5	4	4	4	4	3	1	30
59	2000581	3	3	4	4	1	1	1	1	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	1	30
60	2000582	1	5	5	5	5	5	5	5	2	5	5	5	5	5	5	5	5	5	5	5	5	1	1	5	5	5	5	5	5		29
61	2000741	5	5	5	5	5	5	5	5	5	5	1	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	30
62	2000742	3	3	3	3	3	3	3	3	3	3	3	3																			12

Table B1. Sequences of Representative Patterns over 6 Week: Worker (2)

1	Pattern A	Public Transport Commuting
2	Pattern B	Car Based Multiple Visits
3	Pattern C	Shopping& Leisure
4	Pattern D	Accompanying
5	Pattern E	Work

No	Individual ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	sum
63	2000781	5	1	1	2	2	1	5	5	5	5	5	5	5	5	1	5	5	1	5	5	5	2	5	5	5	1	5				27
64	2000782	4	4	4	3	3	3	4	5	4	2	4	4	1	4	5	4	4	2	5	3	3	4	4	3	3	2	5	4			28
65	2000971	5	1	2	5	1	1	5	1	5	5	4	3	3	4	4	3	3	4	4	5	5	5	5	5	5	5	3	5	5		29
66	2001201	3	3	3	3	3	3	3	4	3	4	3	5	3	3	3																15
67	2001221	5	5	2	5	2	5	1	5	5	5	2	3	5	5	5	5	5	5	2	2	5	5	5	5	5	5	5	5	5		29
68	2001222	3	1	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	5	5	5	5	5	5	4	4		29
69	2001321	5	3	3	3	3	3	3	3	4	3	4	3	4	3	1	3	3	5	3	1	3	3	1	5	5	4	3	3	3	4	30
70	2001371	4	5	1	5	5	4	1	1	2	1	1	1	4	1	5	4	5	1	2	5	4	5	5	1	1	1	1	5	4	4	30
71	2001372	3	3	2	3	4	3	3	2	3	3	3	3	3	3	2	3	4	3	3	3	2	3	3	3	4	4	2	2	2	2	30
72	2001541	1	1	4	1	4	1	1	4	1	3	1	1	1	1	4	4	1	1	1	1	4	1	1	1	1	5	1	1	1	1	30
73	2001542	4	4	1	5	4	1	4	4	5	4	1	4	1	1	4	3	4	1	4	1	4	1	4	1	4	5	4	1	4	4	30
74	2001752	2	1	5	2	5	5	1	2	5	5	5	2	5	2	5	5	5	5	5	1	2	5	5	5	5	5	5	2	5	1	30
75	2002161	5	5	3	4	3	3	4	5	5	4	3	3	5	1	5	5	3	3	4	1	4	5	2	4	1	5	1	4	1	5	30
76	2002491	3	3	3	3	3	3	3	3	3	5	5	5	5	5	2	5	5	1	5	5	5	5	5	5	5	1	5	1	5		29
77	2002512	5	5	5	5	5	5	2	5	5	5	5	5	1	5	5	5	5	5	5	5	5	5	5	5	5	3	5	5	1		29
78	2002772	3	3	4	4	3	3	4	3	4	3	3	4	1	3	5	3	4	4	5	4	1	3	4								23
79	2003331	1	1	1	1	4	4	4	1	1	3	3	4	1	1	1	1	4														17
80	2003351	5	5	5	5	1	3	3	3	5	5	5	5	4	4	3	2	5	5	5	1	5	5	5	5	3						25
81	2003391	5	5	3	3	5	2	2	3	4	5	1	5	4	3	3	3	3	3	3	3	3	3	3	3	3	1	5	5	4	4	30
82	2003392	5	5	3	3	3	5	5	1	5	1	5	1	4	4	3	5	5	5	2	5	5	1	5	5	5	4	3	5	5	4	30
83	2003511	5	5	5	2	1	5	5	3	5	2	2	5	5	5	5	5	5	5	5	5	5	5	5	5	1	5	5	5	5	5	30
84	2003512	5	5	5	5	5	5	5	5	5	5	2	5	5	2	5	5	1	5	5	5	5	5	5	5	5						25
85	2003513	2	2	2	2	2	2	2	2	4	2	2	1	5	1	5	2	2	2	2	5	2	5	2	2	1	5	3	2			28
86	2003541	5	5	4	5	5	5	3	3	5	5	5	5	4	2	2	3	4	2	5	5	5	5	5	5	5	3	3	5			28
87	2010141	2	2	1	5	1	5	5	5	5	5	2	5	5	5	2	5	2	3	4	4	2	5	5	5	1	5	5	5	4		29
88	2010142	5	2	5	5	5	5	1	5	5	5	4	3	2	5	5	5	5	5	4	5	2	4	5	5	5	5	5	1			28
89	2010161	5	5	5	5	5	5	1	5	5	5	5	1	4	5	5	1	5	5	5	5	5	5	5	5	5	5	5	5	5		29
90	2010162	1	1	1	1	4	4	1	1	5	1	5	4	1	1	1	1	1	2	1	4	1	4	1	4	1	4	1	1	5		29

Table B1. Sequences of Representative Patterns over 6 Week: Worker (3)

1	Pattern A	Public Transport Commuting
2	Pattern B	Car Based Multiple Visits
3	Pattern C	Shopping& Leisure
4	Pattern D	Accompanying
5	Pattern E	Work

No	Individual ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	sum
91	2010261	5	5	5	2	2	5	2	5	2	5	2	2	2	2	5	5	5	5	5	5	5	5	5	5	5						25
92	2010262	1	5	5	1	1	1	1	5	1	1	1	1	1	1	1	1	1	5	1	1	1	1	1	1							24
93	2010501	5	5	2	5	5	5	2	5	2	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	2	5	2			28
94	2010732	4	3	4	3	4	4	3	1	3	5	5	5	2	2	5	5	5	5	1	1	5	5	5	5	5	5	1	5	1	4	30
95	2011222	1	1	1	1	1	4	5	1	1	1	1	4	4	4	3	1	1	4	1	5	1	2	4	1	2	1	3	4			28
96	2011722	2	5	2	5	5	1	1	5	2	5	2	5	1	5	5	2	5	1	5	5	5	5	5	5	5	1	2	5	1		29
97	2011871	3	3	3	3	3	3	3	3	3	3	3	3	3																		13
98	2011872	3	3	3	3	3	4	3	3	4	3	4	3	3	4	4	3	3	3	3	3	3	3	3	3	3	3	3	4			28
99	2012361	5	5	5	5	1	1	1	1	1	1	5	4	4	4	3	4	4	4	4	3	3	3	4	3	5	5	5	2	4		29
100	2012362	5	3	1	1	5	1	5	5	5	5	5	5	3	5	5	5	1	5	5	5	5	1									22
101	2012401	2	2	2	2	2	2	2	2	2	5	2	2	5	2	5	5	5	3	5	2	5	5	5	5	5	4	1	3			28
102	2012402	5	5	2	1	5	2	2	5	5	5	5	5	5	5	2	5	2	5	5	1	5	1	1	5	4	1					26
103	2012491	5	5	5	5	1	5	5	5	5	5	5	5	1	5	5	5	1	5	1	5	1	1	1	5	5	5	5	5	1	1	30
104	2012492	1	1	1	1	2	1	4	5	5	1	5	5	1	5	1	5	1	5	5	1	5	1	1	1	5	1	5	1	5	1	30
105	2012991	5	5	5	2	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	2	5	5		29
106	2012992	1	5	5	5	1	4	3	3	3	3	1	3	4	4	3	1	4	3	1	5	3	1	5	5	5	5	1	5	3		29
107	2013341	2	5	5	5	2	5	5	5	5	5	5	5	2	5	2	5	5	5	5	5	5	5	5	5	5	5	5	5	1	5	30
108	2013471	5	5	5	5	5	5	1	1	5	5	1	3	5	1	5	5	1	5	5	1	1	1	5	5	5	5	5	4	2		29
109	2013472	1	5	4	1	2	1	1	1	1	2	5	5	1	1	5	1	2	1	1	2	1	1	1	4	4						25

APPENDIX B:

Table B2 Sequences of Representative Patterns over 6 Week: Non-Worker (1)

1	Pattern A	Public Transport Commuting
2	Pattern B	Car Based Multiple Visits
3	Pattern C	Shopping& Leisure
4	Pattern D	Accompanying
5	Pattern E	Work

No	Individual ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	sum
1	1000031	1	1	4	4	4	1	1	1	1	4	4	3	4	3	3	4	1	4	3	4	4	4	3	4	4	4	4	4			28
2	1000032	3	3	3	3	3	3	4	3	3	3	3	3	3	3	1	3	3	3	3	3	3	3	3	3	3	3	4	4	4		29
3	1000551	3	3	3	3	3	3	3	3	4	3	3	3	3	4	3	3	3	3	3												19
4	1000552	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3										21
5	1001071	3	3	3	3	3	3	4	4	3	3	3	4	3	3	3	3	3	3	3	3	4	3	3	3	4	3	3				27
6	1001072	3	3	4	4	3	3	4	4	3	4	4	3	3	3	3	3	4	4	3												19
7	1001161	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	3	4	3	3	4	3	3	3	4	4	4	3	3		29
8	1001251	3	3	4	4	3	4	4	1	4	4	4	1	4	1	4	4	3	4	1	4	3	4	4	4	4	3	1	5	1	4	30
9	1001441	3	4	3	3	4	3	3	3	4	3	3	3	4	3	3	4	4	3	3	4	4	3	4								23
10	1001451	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3														17
11	1001471	3	3	4	3	3	3	3	4	3	3	3	3	3	4	3	3	4	4	4	3	3	4	4								23
12	1001591	3	3	3	3	4	3	4	3	3	4	3	3	4	4	3	4	4	4	4	3	4	4	3	4	4	3	4	4	4		29
13	1001721	3	4	4	3	4	3	4	3	4	4	3	4	3	3	3	3	4	3	3	3	3	3	3	3	4	3	3	3	3	4	30
14	1001722	3	3	3	1	3	3	3	4	3	3	3	3	3	3	3	3	3	1	3	3	3	3	4	3	4	3	3	3	3		29
15	1001951	4	4	4	4	4	3	3	3	3	3	4	3	4	3	4	4	4	4	3	3	3	3	4	3	4	4	4				27
16	1002881	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	4	3	4	4	4	30
17	1002882	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	4	3	4	30
18	1003181	4	4	1	4	4	4	4	1	4	4	4	1	4	4	5	4	1	3	1	1	1	4									22
19	1003241	3	3	3	3	3	3	4	3	4	4	3	3	4	3	4	4	3	3	3	3	3	5	4								23
20	1003341	3	1	4	3	5	4	3	3	3	4	4	3	4	3	4	3	3	3	4	4	3	3	3	3	4						25
21	1003342	3	3	1	4	3	5	4	3	3	3	4	4	3	5	3	3	4	3	4	4	3	3	3	4	5						25
22	1003491	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3	3	3	3	3	3	3	3	4	3	3	4			28
23	1003492	3	3	3	3	3	3	3	4	3	3	3	3	3	4	4	4	3	3	3	3	4										21
24	1003502	4	4	1	4	3	1	3	3	3	1	1	3	4	3	1	3	3	3	1	4	3	4	3	4	3	1	1	1			28
25	1003511	4	4	3	3	4	3	3	3	3	4	3	4	3	3	3	3	3	3	3	4	3	4	4	2							24
26	1003512	4	4	3	3	4	3	3	3	4	3	3	3	3	3	4	4	4	4	3	4	2										21

Table B2 Sequences of Representative Patterns over 6 Week: Non-Worker (2)

1	Pattern A	Public Transport Commuting
2	Pattern B	Car Based Multiple Visits
3	Pattern C	Shopping& Leisure
4	Pattern D	Accompanying
5	Pattern E	Work

No	Individual ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	sum
27	1010101	3	4	3	3	3	3	4	3	3	3	3	3	3	3	4	3	3	4													18
28	1010102	3	3	3	4	3	3	3	3	3	3	3	4	3	3	3	3	4	3	3	3	3	3	4	4	3	3	4				27
29	1010332	3	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	1	3	28
30	1011001	4	3	3	3	3	3	4	1	1	3	3	3	3	3	3	4	3	3	3	3	3	3	3	3	3	3	5	3	3	3	30
31	1011722	4	3	3	4	1	4	4	3	4	4	4	4	1	4	4	3	4	4	3	4	4	3	4	3	3	4	3	3	3	4	30
32	1012201	3	4	3	1	3	3	4	3	3	3	4	4	1	3	1	3	3	4	3	1	4	3	2	1	1						25
33	1012621	3	3	3	4	4	3	3	3	4	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3	4						25
34	1012622	3	3	3	3	3	3	3	3	4	3	3	3	3																		13
35	1012691	3	3	4	3	3	3	4	3	3	1	3	3	3	3	3	3	3	3	3	3	3	3	4								23
36	1012971	3	4	3	3	3	4	4	3	1	4	3	4	4	3	3	3	3	3	4	3	4	3	3	4	3	4					26
37	1013231	4	5	1	3	1	1	4	1	1	5	4	4	1	1	1	4	3	5	4	3	4	1	3	1	5	4	4	1			28
38	1013271	3	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3							28
39	1013272	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3														17
40	2000062	3	3	4	3	3	3	3	3	4	3	4	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3	3	4			28
41	2000182	3	3	4	3	3	3	3	4	3	4	3	1	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	30
42	2000222	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1																15
43	2000282	1	3	4	1	3	3	3	4	3	3	3	3	3	1	4	4	3	4	4	4	3	1	4	4	3	4	1	5			28
44	2000583	3	3	3	4	3	3	3	4	3	3	3	4	3	3	3	3	1	1	1	1	1	4	4								23
45	2000611	3	3	3	3	3	3	3	3	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4			28
46	2000613	4	3	5	3	3	3	4	4	4	3	3	4	1	1																	15
47	2000881	3	3	3	3	3	3	3	3	3	3	1	1	4																		13
48	2000972	4	4	4	4	3	4	3	3	4	3	3	1	3	1	1	1	1	1	3	3	3	3	1	4							24
49	2001101	3	4	1	3	3	3	4	3	4	3	3	3	3	3	3	3	4	3	4	3	4	1	3	4	1	5					26
50	2001431	1	1	1	1	1	1	1	4	4	4	1	4	2	2	5	1	5	5	2	5	5	5	5	5	5	5	5	5	5		29
51	2001591	3	3	3	4	3	3	3	3	3	3	3	3	3	4	3	3	3	3	3	4											20
52	2001592	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3																15
53	2002162	4	3	4	1	4	4	4	4	3	4	4	3	5	1	1	4	4	4	1	1	4	5	4	4	4	1	4	4			28

Table B2 Sequences of Representative Patterns over 6 Week: Non-Worker (3)

1	Pattern A	Public Transport Commuting
2	Pattern B	Car Based Multiple Visits
3	Pattern C	Shopping& Leisure
4	Pattern D	Accompanying
5	Pattern E	Work

No	Individual ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	sum
54	2002511	4	3	3	3	4	4	4	3	4	4	5	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3		29
55	2002601	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	1							24
56	2002602	3	3	3	3	3	3	3	3	3	3	3	4	3	3	1																16
57	2002951	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3															16
58	2003321	5	4	4	4	4	5	5	1	1	5	1	5	1	2	1	4	1	3	4	1	4	2	1	4	5	5	2	2	3	5	30
59	2003322	5	1	4	1	4	5	1	1	5	5	5	5	1	5	2	5	5	5	1	1	5	1	1	1	1	2	1	1	1	4	30
60	2003352	4	3	4	3	5	5	5	3	4	4	3	3	5	5	5	5	1	4	3	4	4	3	3								23
61	2003393	5	1	5	1	2	1	1	5	4	4	1	1	1	4	4	1	1	4	1	1	3	1	1	4	4	5	1	1	4	5	30
62	2010221	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3														17
63	2010222	3	3	3	3	3	4	4	3	3	3	4																				11
64	2010502	4	3	3	4	4	4	4	3	2	3	4	3	4	3	3	4	3	4	3	3	3	4	3	3	4	3	3	4	3		29
65	2011051	1	4	1	4	4	4	4	1	1	4	4	1	4	4	1	1	3	1	3	1	1	4	3	3	4	4	4	4	1	4	30
66	2011052	3	1	4	1	3	3	3	3	3	3	4	4	3	4	3	3	3	3	4	3	3	1	3	1	3	1					26
67	2011111	3	1	1	1	5	5	5	4	3	4	2	4	1	5	3	1	5	1	4	4	4										21
68	2011221	1	1	1	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	5	1	2	1	1	30
69	2011401	3	3	3	4	4	4	4	4	1	4	4	4	4	4	3	4	4	4	3	4	4	4	3	4	3	1	4	3	4	3	30
70	2011402	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3	4	3	3	3	3											20
71	2011791	3	3	1	3	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	3	3	4	4	3	4	3	3	3	3	4	30
72	2011821	4	3	3	3	4	3	3	4	3	3	4	4	4	3	3	4	4	3	3	3	3	4	4	3	4	4	3	4			30
73	2011861	4	4	4	4	3	3	4	3	3	4	4	4	3	3	3	3	3	4	3	4	3	3	3								23
74	2011862	4	3	4	4	4	4	3	3	4	3	3	4	3	4	4	3	3	3	3	3	3	3									22
75	2011971	4	4	3	5	3	4	4	4	4	3	4	3	3	4	3	4	4	4	4	3	4	4	4	4	4	3	4	3	4	5	30
76	2012061	4	5	3	3	5	4	3	3	3	3	1	3	4	1	1	2	1	5	1	5	1	4	1	1	1	1	3	1	1	1	30
77	2012481	3	3	3	1	1	5	5	4	5	3	5	4	5	3	2	5	5	3	3	4	1	3	1	3	1	1	3	4	1	5	30
78	2012482	3	3	1	3	3	5	3	5	3	3	3	3	3	3	5	3	3	3	1	3	1	3	3	3	3	4	1	3	5		29
79	2012761	1	3	1	2	4	1	3	4	3	3	4	3	5	5	5	5	5	5	5	5	5	3	3	3	5	1	4	5			28
80	2012851	3	3	3	3	3	3	3	3	3	4																					10

Table B2 Sequences of Representative Patterns over 6 Week: Non-Worker (4)

1	Pattern A	Public Transport Commuting
2	Pattern B	Car Based Multiple Visits
3	Pattern C	Shopping& Leisure
4	Pattern D	Accompanying
5	Pattern E	Work

No	Individual ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	sum
81	2012972	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3					26
82	2013251	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3												19
83	2013321	4	3	3	4	3	3	3	4	4	4	3	4	3	4	4	3	3	3	3	3	3	3	3	4	3	3	3				27
84	2013322	3	3	4	3	3	4	3	3	4	3	4	3	1	4	3	3	3	3	3	3	3	3	3	4	1	4	4				27
85	2013381	4	1	4	1	1	3	3	4	1	1	4	3	1	3	4	4	4	1	1	3	5	4	4	5	3	5	5	4	4	4	30
86	2013382	4	4	4	4	3	3	4	4	3	3	1	3	3	4	1	4	4	5	3	1	5	4	3	3	3	3	4				27

APPENDIX C:

C1. Markov theorems

For regular Markov chain two important theorems relating to the equilibrium properties are provided by Kemeny and Shell (1967, pp 69-98).

Theorem 1

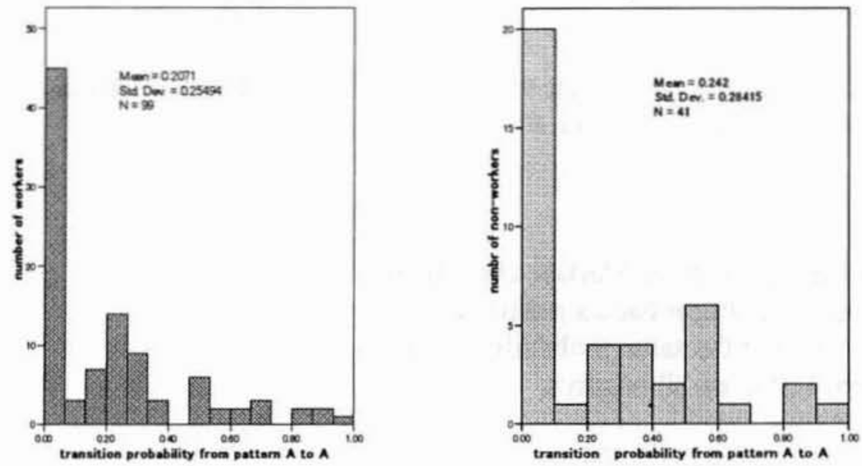
If **P** is transition matrix for regular Markov chain then:

1) The power of **P** approach a matrix **A**
2) Each row **A** is the same probability vector α
3) Elements of α are all positive.

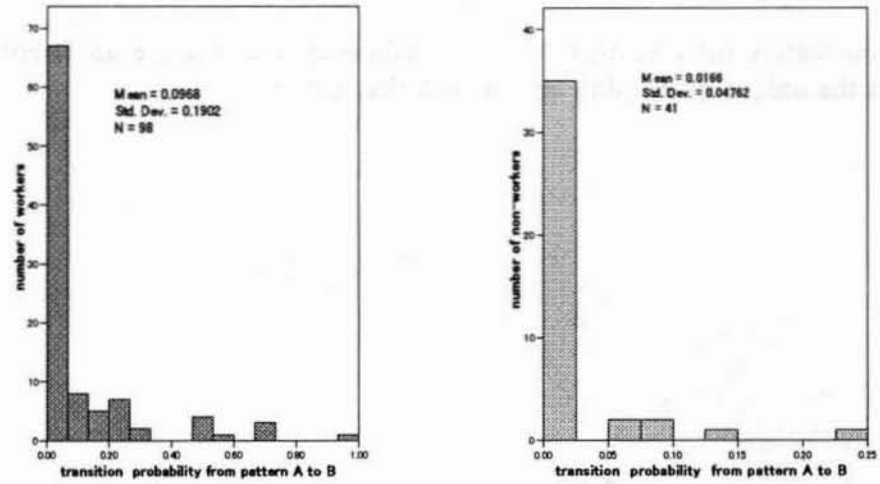
Theorem 2

If **P** is a transition matrix for a regular Markov chain and **A** and α are as Theorem 1, the unique vector α is the unique probability vector such that α P=α.

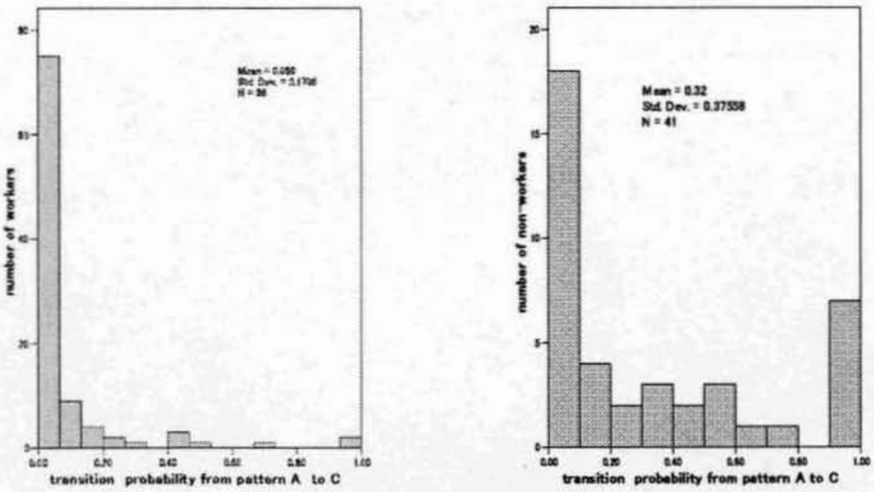
C3. Distribution of Individual-Based Transition Probabilities



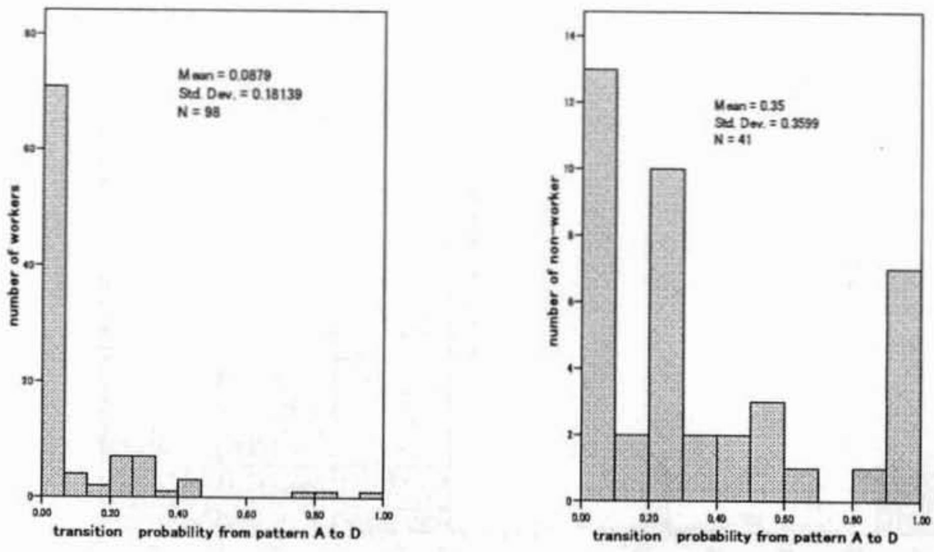
Public Transport Commuting- Public Transport Commuting



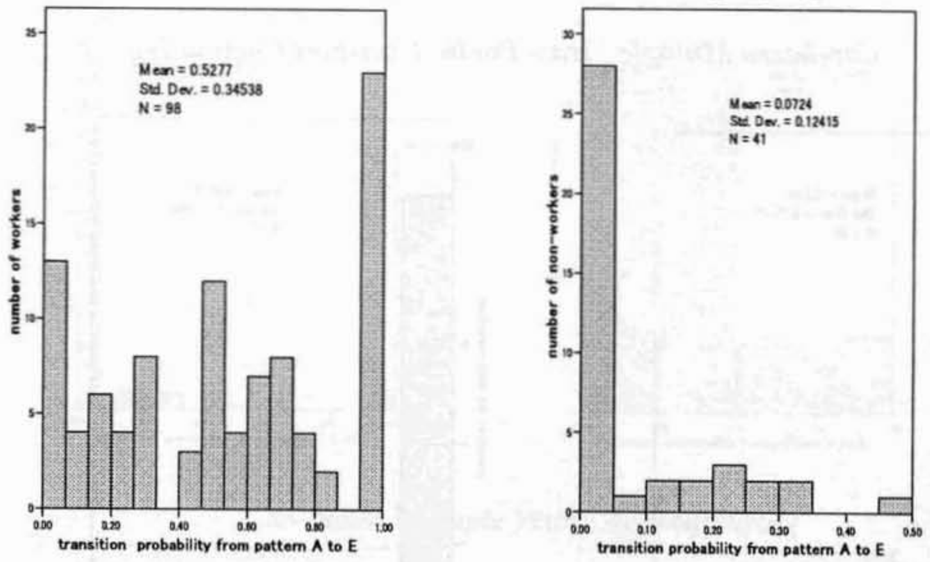
Public Transport Commuting- Car–based Multiple Visits



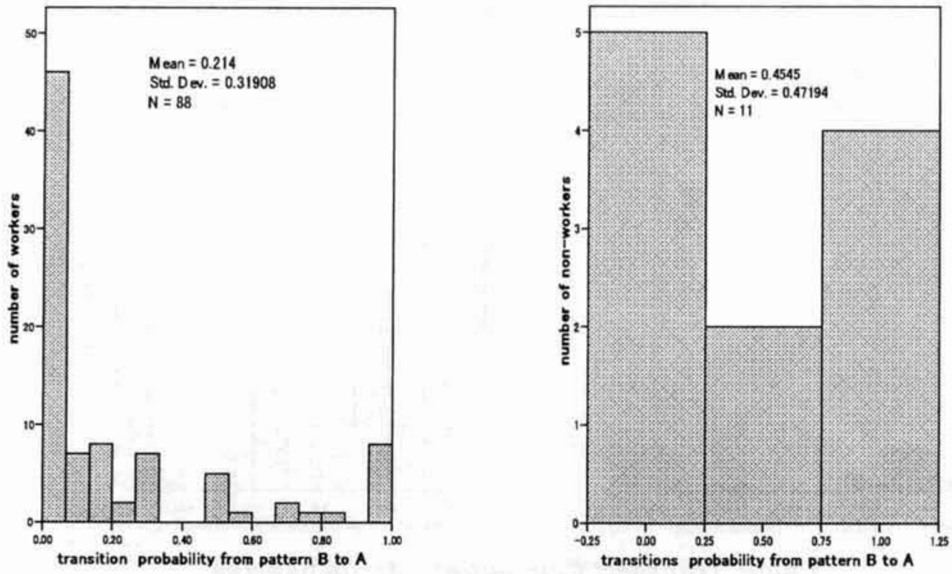
Public Transport Commuting- Shopping & Leisure



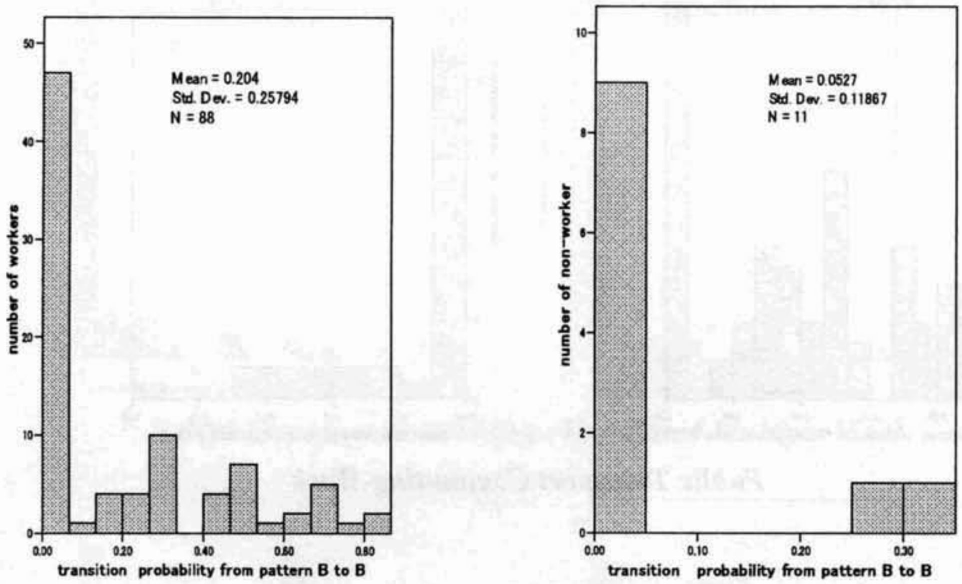
Public Transport Commuting- Accompanying



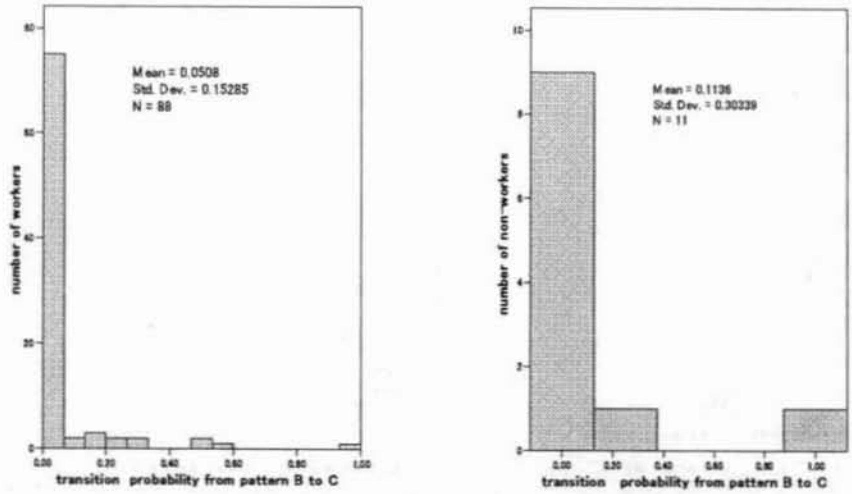
Public Transport Commuting-Work



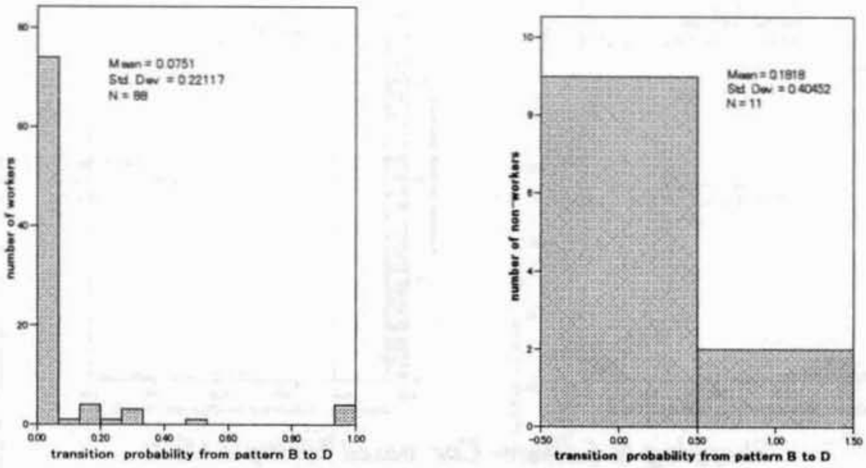
Car–based Multiple Visits- Public Transport Commuting



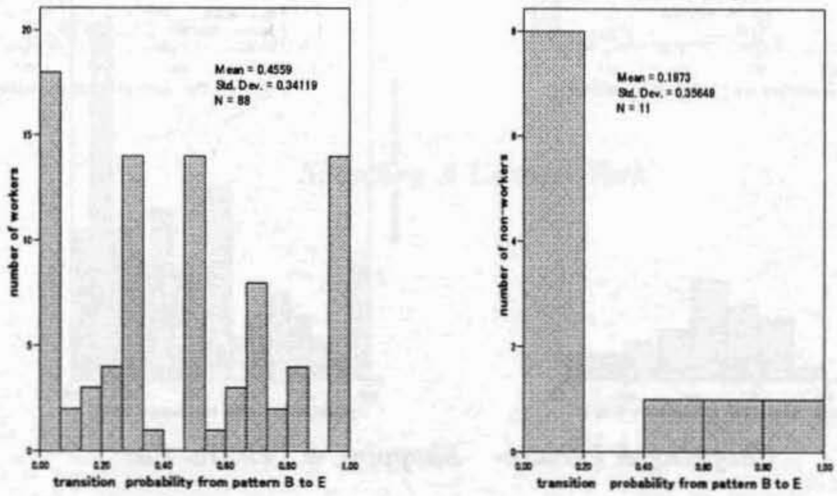
Car–based Multiple Visits- Car–based Multiple Visits



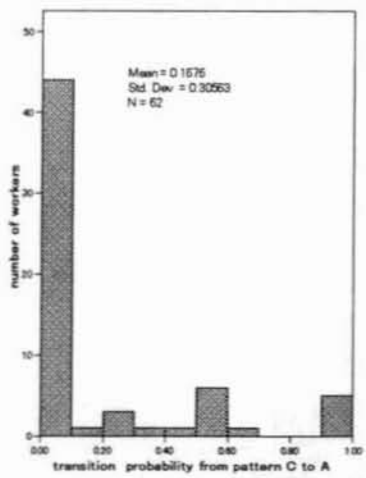
Car–based Multiple Visits- Shopping & Leisure

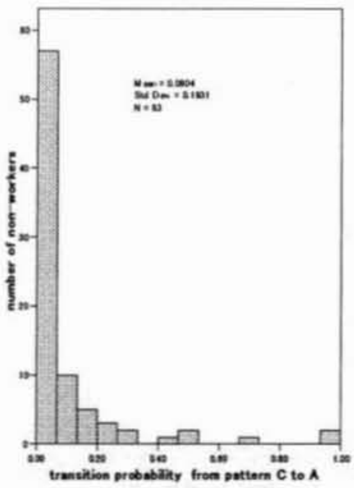


Car–based Multiple Visits- Accompanying

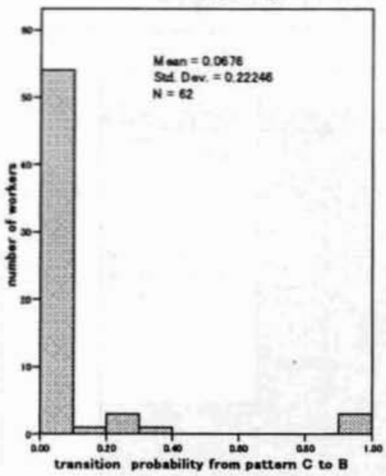


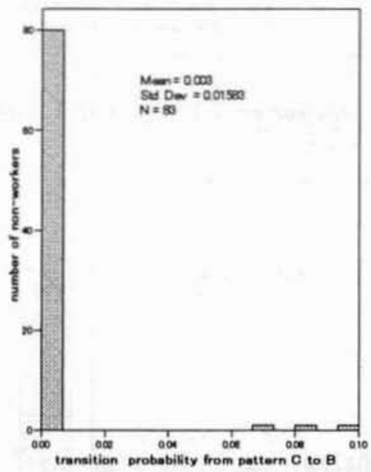
Car–based Multiple Visits-Work



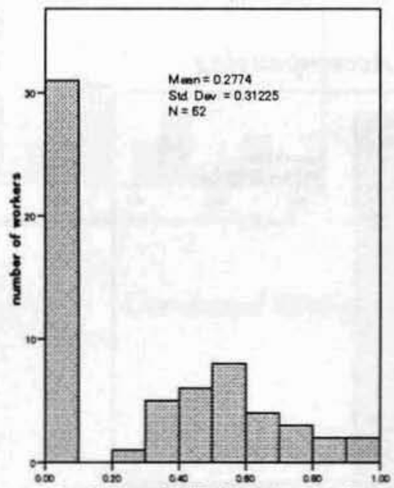


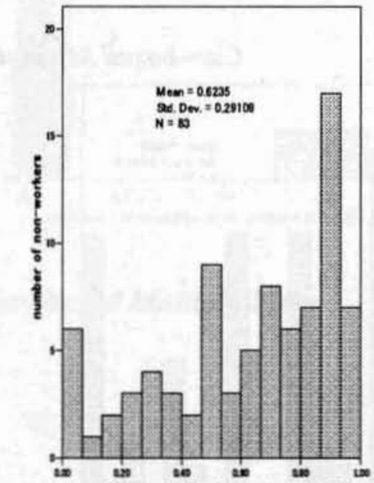
Shopping & Leisure Public Transport Commuting



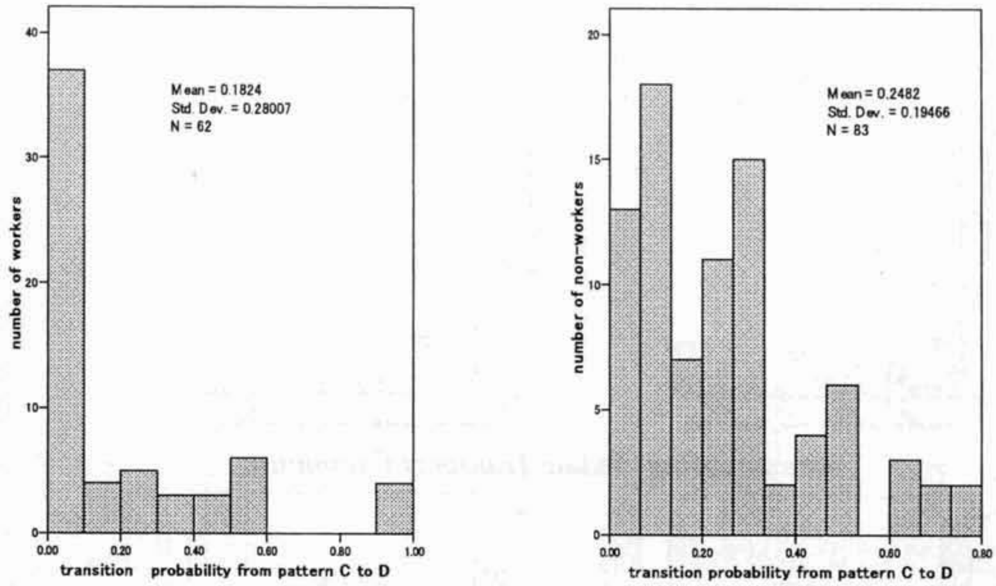


Shopping & Leisure- Car–based Multiple Visits

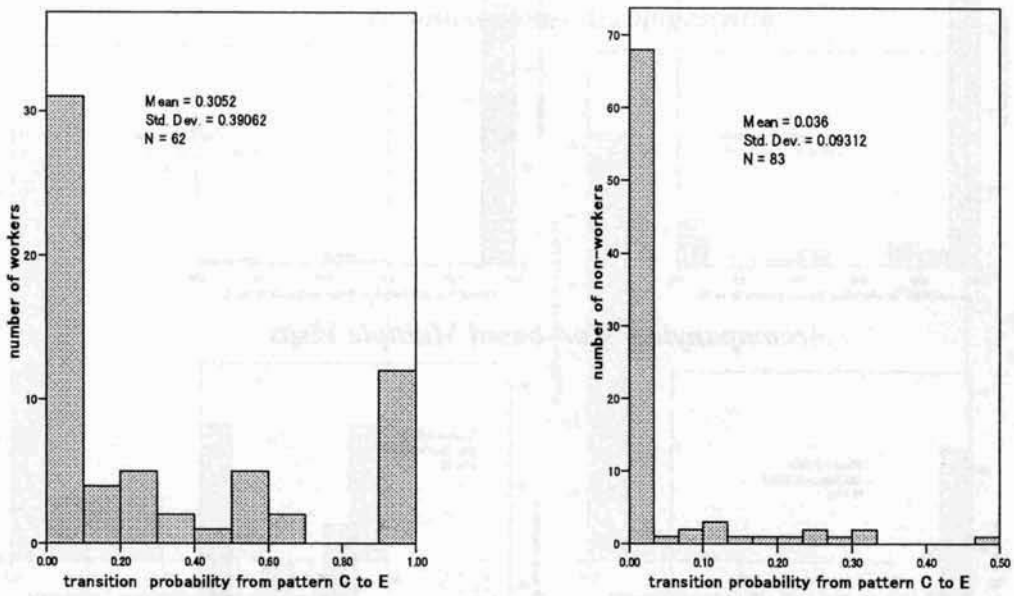




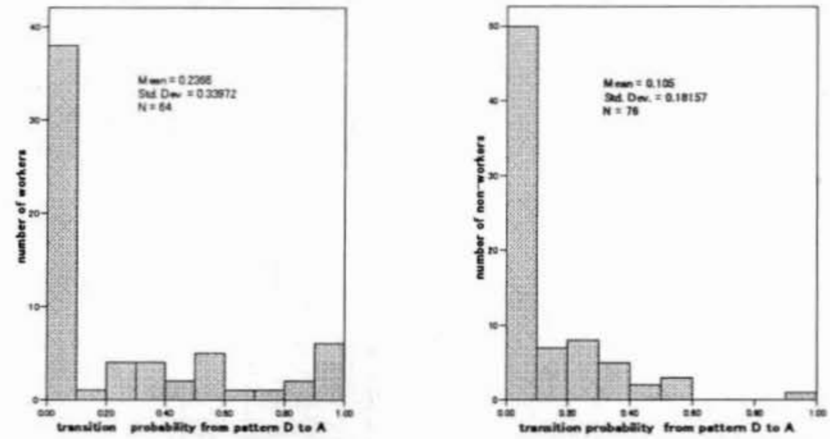
Shopping & Leisure- Shopping & Leisure- Car



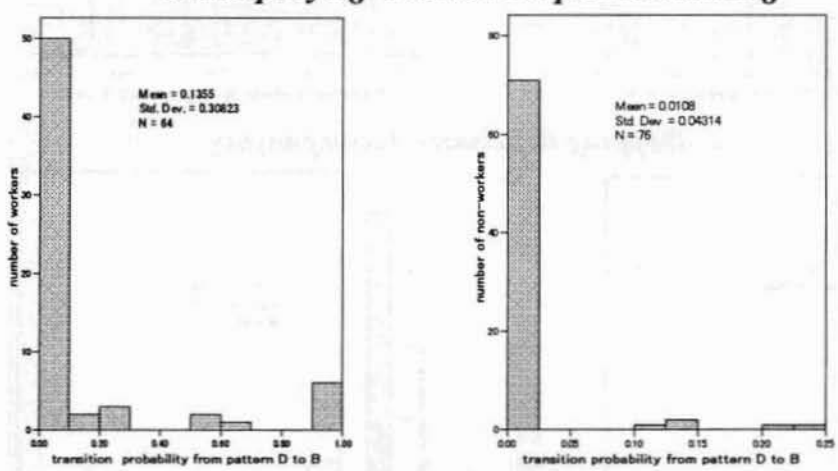
Shopping & Leisure- Accompanying



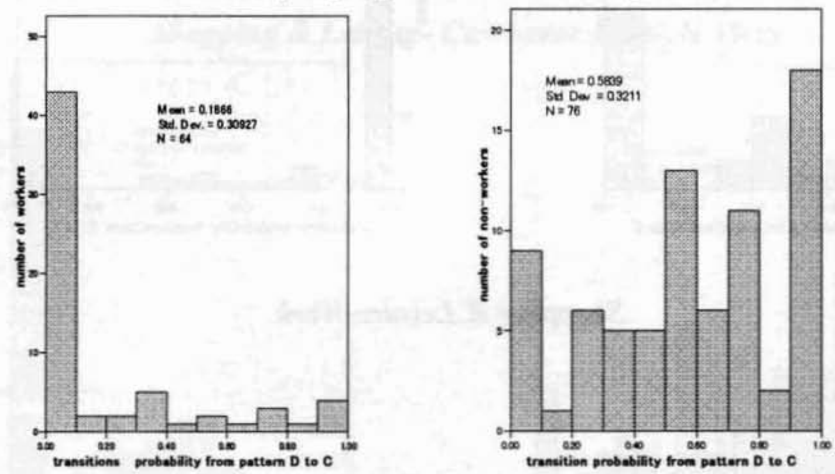
Shopping & Leisure-Work



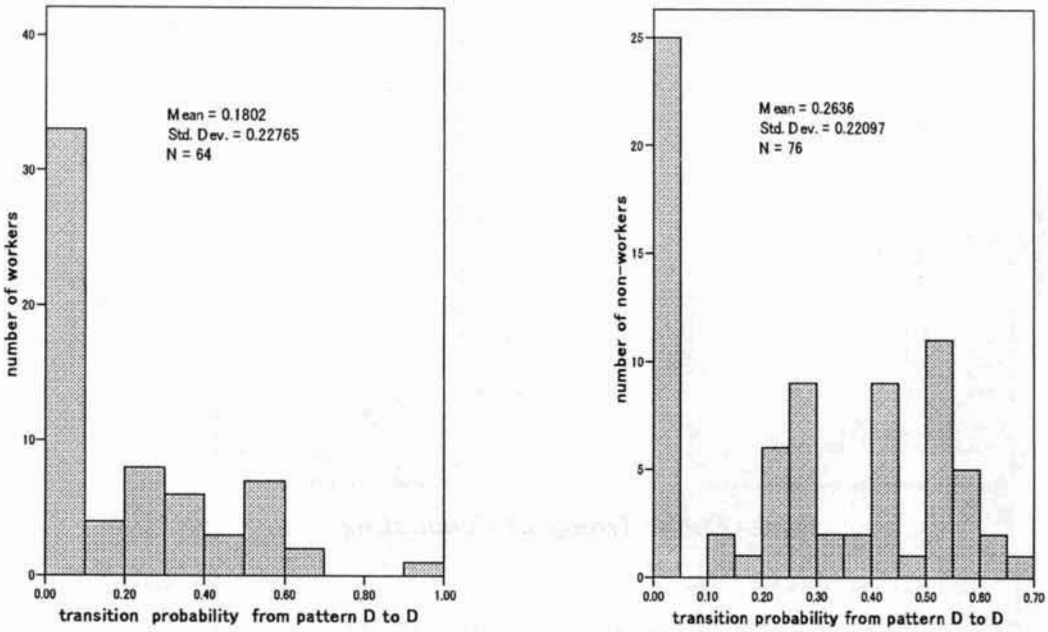
Accompanying- Public Transport Commuting



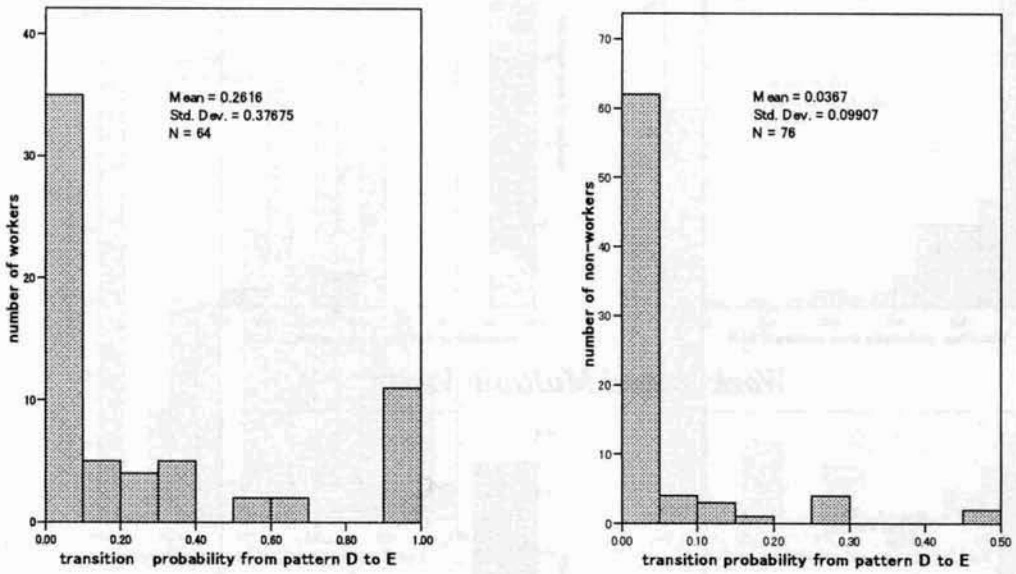
Accompanying- Car–based Multiple Visits



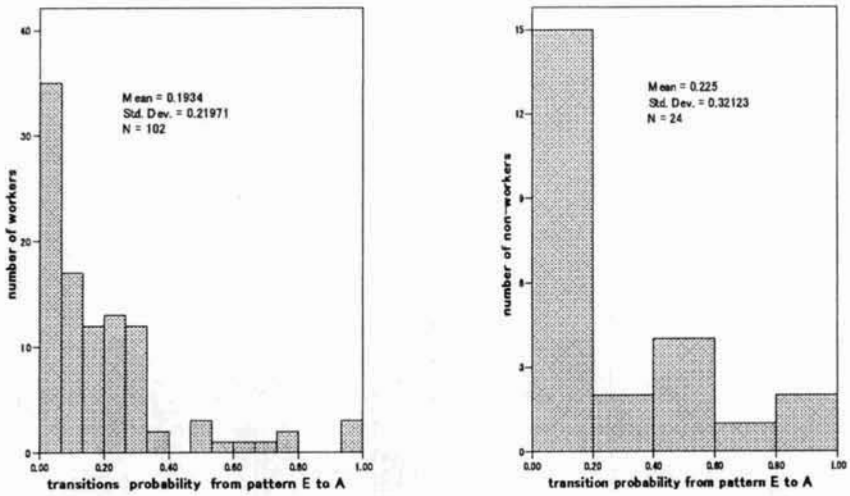
Accompanying- Shopping & Leisure



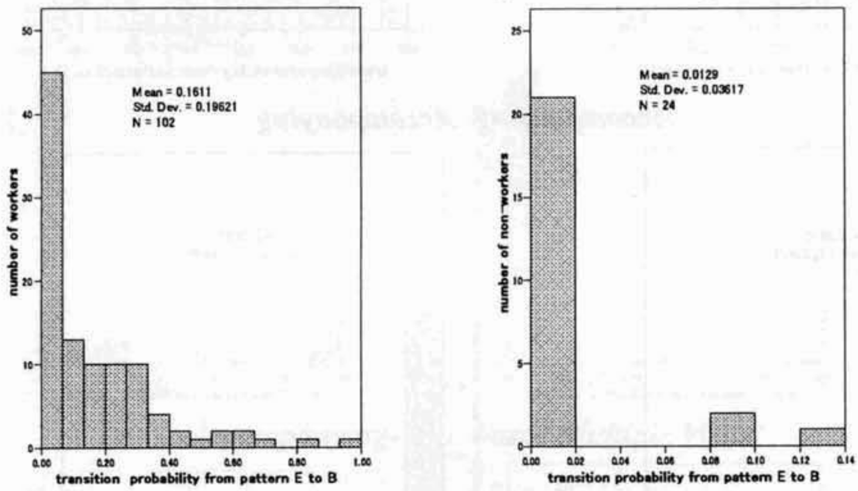
Accompanying- Accompanying



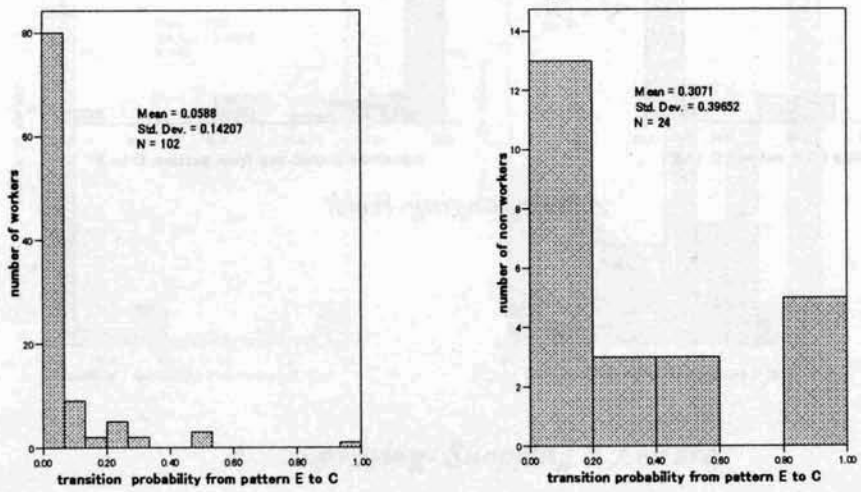
Accompanying-Work



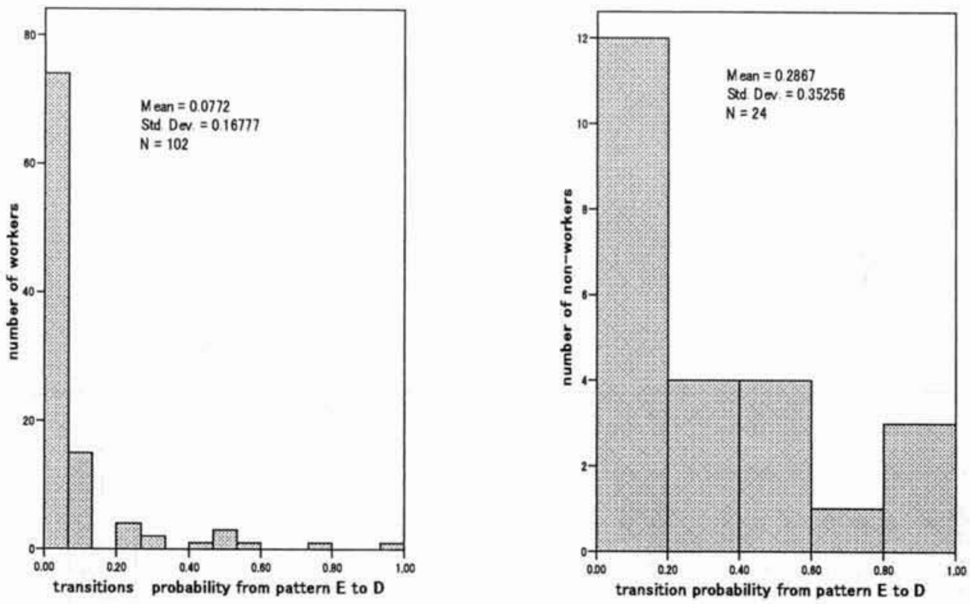
Work- Public Transport Commuting



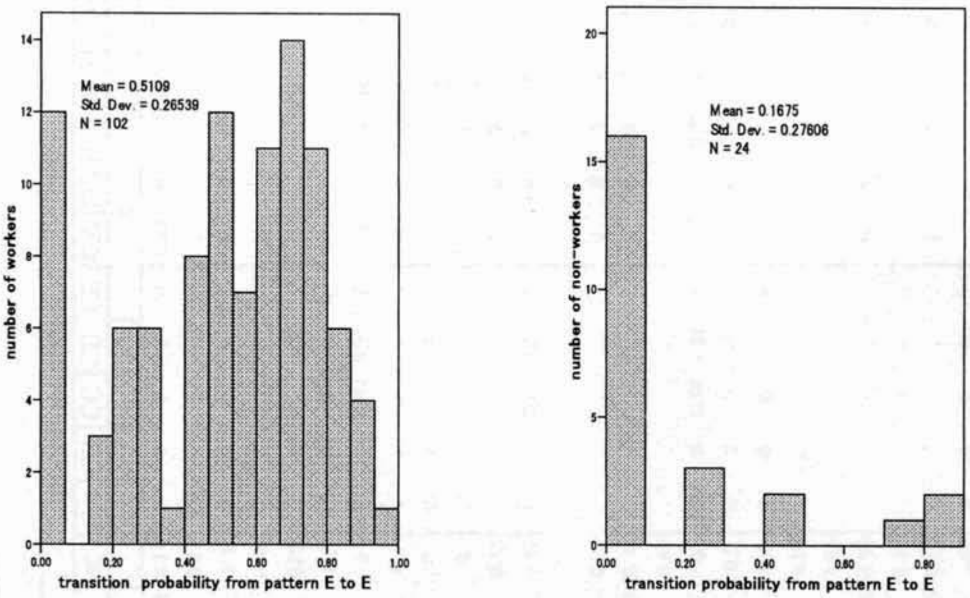
Work- based Multiple Visits



Work- Shopping & Leisure



Work- Accompanying



Work- Work

TABLE C1. Individual-Based Transition Matrix: Workers(1)

No	Individual ID	Transition Matrix																								
		AA	AB	AC	AD	AE	BA	BB	BC	BD	BE	CA	CB	CC	CD	CE	DA	DB	DC	DD	DD	EA	EB	EC	ED	EE
1	1000091	0.25	0	0	0.75	0	0	0.71	0	0.14	0.14	0	0	0	1	0	0.23	0	0.08	0.69	0	0	1	0	0	0
2	1000481	0	0.67	0	0	0.33	0.33	0.44	0	0	0.22	.	.	.	.	.	.	.	.	.	.	0	0.21	0	0	0.79
3	1000521	0	0	0	0	1	0	0.5	0	0	0.5	0	0	0	0	1	0	0	0	0	1	0.05	0.1	0.05	0.05	0.75
4	1000531	0	0	0	0	1	0	0.14	0	0	0.86	0	0	0.33	0	0.67	.	.	.	.	.	0.06	0.28	0.11	0	0.56
5	1000761	0	0.67	0	0	0.33	0.09	0.83	0	0	0.09	.	.	.	.	.	.	.	.	.	.	0.33	0.33	0	0	0.33
6	1000851	0	0	0	0	1	0	0.33	0.17	0	0.5	0.5	0	0	0	0.5	.	.	.	.	.	0.05	0.21	0.05	0	0.68
7	1000852	0.17	0	0.17	0.17	0.5	0	0	1	0	0	0	0	0.67	0.33	0	0.5	0.25	0	0.25	0	0.6	0	0	0	0.4
8	1001041	0.27	0.09	0	0	0.64	0	0.5	0	0	0.5	.	.	.	.	.	.	.	.	.	.	0.5	0	0	0	0.5
9	1001042	0.31	0	0.08	0	0.62	1	0	0	0	0	0	1	0	0	0	.	.	.	.	.	0.57	0	0	0	0.43
10	1001051	0.58	0.08	0	0	0.33	1	0	0	0	0	.	.	.	.	.	.	.	.	.	.	0.31	0	0	0	0.69
11	1001053	0.22	0.22	0	0	0.56	0.67	0	0	0	0.33	.	.	.	.	.	1	0	0	0	0	0.25	0.06	0	0.06	0.63
12	1001172	0	0.5	0	0	0.5	0.33	0.33	0	0	0.33	0	0	0.67	0.33	0	1	0	0	0	0	0.15	0.08	0.08	0	0.69
13	1001452	0.56	0	0	0	0.44	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	0.16	0.05	0	0	0.79
14	1001472	0	1	0	0	0	0.06	0.59	0.06	0	0.29	.	.	.	.	.	0	0	0	0	1	0	0.86	0	0	0.14
15	1001541	0	0	0	0	0	0	0	0	0.25	0.75	.	.	.	.	.	0	0	0	0	1	0	0.29	0	0	0.71
16	1001592	0	0.5	0	0	0.5	0.08	0.25	0	0	0.67	.	.	.	.	.	.	.	.	.	.	0.07	0.47	0	0	0.47
17	1001832	0	0	0.4	0.4	0.2	0	0	0	1	0	0.33	0	0.58	0.08	0	0.25	0	0.75	0	0	.	.	.	.	.
18	1001891	0.2	0.2	0	0.2	0.4	0.17	0.33	0	0	0.5	0	0	0	0	1	1	0	0	0	0	0.13	0.19	0.06	0	0.63
19	1001892	0.22	0.11	0.11	0	0.56	0.5	0	0	0	0.5	1	0	0	0	0	.	.	.	.	.	0.33	0.2	0	0	0.47
20	1001893	0.2	0.2	0	0	0.6	0.29	0.14	0	0	0.57	.	.	.	.	.	.	.	.	.	.	0.18	0.29	0	0	0.53
21	1001941	0	0	0	0	1	0.17	0	0	0	0.83	.	.	.	.	.	.	.	.	.	.	0.12	0.41	0	0	0.47
22	1001961	0.33	0	0	0	0.67	0.08	0.46	0	0.08	0.38	.	.	.	.	.	0	0	0	0	1	0.08	0.58	0	0	0.33
23	1002291	0	0.5	0	0	0.5	0.19	0.63	0	0	0.19	.	.	.	.	.	.	.	.	.	.	0.14	0.57	0	0	0.29
24	1002311	1	0	0	0	0	0.05	0.76	0	0.05	0.14	.	.	.	.	.	0	1	0	0	0	0	0.6	0	0	0.4
25	1002901	0.5	0	0	0	0.5	0	0.33	0	0	0.67	0	0	0	0	1	.	.	.	.	.	0.25	0.25	0.06	0	0.44
26	1002931	0.36	0.09	0	0	0.55	0.5	0	0	0	0.5	.	.	.	.	.	.	.	.	.	.	0.36	0.14	0	0.07	0.43
27	1003091	0	0.5	0	0	0.5	0.08	0.69	0	0	0.23	0	0	0	0	1	.	.	.	.	.	0	0.31	0.08	0	0.62
28	1003201	0	0	0	0	1	0.17	0.33	0	0	0.5	.	.	.	.	.	.	.	.	.	.	0.06	0.18	0	0	0.76
29	1003351	0.25	0	0	0	0.75	0	0	0.25	0	0.75	.	.	.	.	.	0	1	0	0	0	0.15	0.15	0	0.05	0.65
30	1003411	0.67	0	0	0.33	0	0	0	0.5	0	0.5	0	0	0.4	0	0.6	0.13	0.13	0	0.5	0.25	0	0.14	0.14	0.57	0.14

TABLE C1. Individual-Based Transition Matrix: Workers(2)

No	Individual ID	AA	AB	AC	AD	AE	BA	BB	BC	BD	BE	CA	CB	CC	CD	CE	DA	DB	DC	DD	DD	EA	EB	EC	ED	EE
31	1003412	0.14	0.14	0.43	0.14	0.14	0	0	0	1	0	0.4	0	0.5	0	0.1	0.33	0	0.33	0	0.33	0.33	0	0.33	0.33	0
32	1003493	0.92	0.04	0	0.04	0	1	0	0	0	0	.	.	.	.	.	1	0	0	0	0	1	0	0	0	0
33	1003501	0.22	0.22	0	0.33	0.22	0	0	0	0.33	0.67	0	0	0	1	0	0.75	0	0	0.13	0.13	0.13	0.13	0.13	0.25	0.38
34	1003521	0	0	0	0	1	0.13	0.25	0	0	0.63	.	.	.	.	.	.	.	.	.	.	0.13	0.31	0	0	0.56
35	1010331	0.2	0	0.2	0	0.6	0.5	0	0	0	0.5	0	0	0	0	1	.	.	.	.	.	0.14	0.1	0	0	0.76
36	1010561	0.33	0.11	0	0.22	0.33	0	0	0	0	1	.	.	.	.	.	0.33	0	0	0.33	0.33	0.31	0	0	0.08	0.62
37	1011351	0.17	0.17	0	0	0.67	0.17	0.33	0.17	0	0.33	.	.	.	.	.	.	.	.	.	.	0.3	0.3	0	0	0.4
38	1011721	0	.	.	.	.	0	0.63	0	0.06	0.31	.	.	.	.	.	0	1	0	0	0	0	0.36	0	0.09	0.55
39	1012001	0	0	0	0.33	0.67	0	0.5	0	0.17	0.33	.	.	.	.	.	0	1	0	0	0	0.17	0.06	0	0	0.78
40	1012202	0.3	0.1	0.1	0.4	0.1	0.33	0	0	0	0.67	0.67	0.33	0	0	0	0.4	0.2	0.2	0.2	0	0.67	0	0.33	0	0
41	1012231	0	0	0	0	1	0.17	0.17	0	0	0.67	.	.	.	.	.	0	0	0	0	1	0.05	0.26	0	0.05	0.63
42	1012552	0.13	0	0	0.38	0.5	.	.	.	.	.	.	.	.	.	.	0	0	0	0	1	0.39	0	0	0.06	0.56
43	1012972	0.2	0	0	0	0.8	0	0	0.33	0	0.67	0	0	0.67	0	0.33	.	.	.	.	.	0.33	0.25	0	0	0.42
44	1013201	0.17	0	0.17	0	0.67	1	0	0	0	0	0.5	0	0	0	0.5	0	0	0	0	1	0.17	0.06	0.06	0.06	0.67
45	1013261	0	0.33	0.33	0	0.33	0.67	0	0	0	0.33	0	0	0.33	0.33	0.33	0.5	0	0	0	0.5	0	0.17	0	0.08	0.75
46	1013351	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0.33	0.67	0.11	0.05	0.05	0.11	0.68
47	1013381	0.33	0	0	0	0.67	0	0.5	0	0	0.5	0	0	0	0	1	.	.	.	.	.	0.1	0.05	0.05	0	0.81
48	1013391	0.13	0.25	0.13	0	0.5	0.86	0	0	0.14	0	0	0	0.33	0	0.67	0	0.5	0	0.5	0	0.17	0.67	0	0	0.17
49	1013393	0.5	0.17	0.08	0	0.25	0.33	0.33	0	0	0.33	1	0	0	0	0	.	.	.	.	.	0.33	0.33	0	0	0.33
50	2000061	0.63	0	0.13	0.13	0.13	.	.	.	.	.	0.25	0	0.75	0	0	0	0	1	0	0	0	0	0	0.5	0.5
51	2000171	0	0	0	0	1	0.11	0.44	0.11	0	0.33	0	0	0	0	1	.	.	.	.	.	0.13	0.38	0	0	0.5
52	2000181	0	0	0	0	1	1	0	0	0	0	.	.	.	.	.	.	.	.	.	.	0.12	0.04	0	0	0.84
53	2000191	0.14	0.57	0	0	0.29	0.56	0.11	0.11	0	0.22	0	0.25	0.5	0.25	0	0	0	1	0	0	0.14	0.43	0	0	0.43
54	2000212	0	0	0	0	1	0	0	0	0.17	0.83	.	.	.	.	.	0	0	0	0	1	0.06	0.35	0	0.06	0.53
55	2000221	0.6	0	0.4	0	0	.	.	.	.	.	0.5	0	0.33	0.17	0	0.25	0	0	0.5	0.25	0	0	0.5	0	0.5
56	2000281	.	.	.	.	.	0	0.71	0	0	0.29	.	.	.	.	.	0	0	0	0	1	0	0.36	0	0.09	0.55
57	2000482	0.17	0	0	0	0.83	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	0.2	0.15	0	0	0.65
58	2000501	0.33	0	0.17	0.33	0.17	.	.	.	.	.	0.25	0	0	0.5	0.25	0.09	0	0.09	0.45	0.36	0.25	0	0.25	0.25	0.25
59	2000581	0.89	0.05	0	0.05	0	0.2	0.8	0	0	0	0	0	0.5	0.5	0	0.67	0	0	0.33	0	.	.	.	.	.
60	2000582	0.33	0	0	0	0.67	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	0.04	0.04	0	0	0.92
61	2000741	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.04	0	0	0	0.96
62	2000742	.	.	.	.	.	.	.	.	.	.	0	0	1	0	0	.	.	.	.	.	.	.	.	.	.

TABLE C1. Individual-Based Transition Matrix: Workers(3)

No	Individual ID	Transition Matrix																								
		AA	AB	AC	AD	AE	BA	BB	BC	BD	BE	CA	CB	CC	CD	CE	DA	DB	DC	DD	DD	EA	EB	EC	ED	EE
63	2000781	0.17	0.17	0	0	0.67	0.33	0.33	0	0	0.33	.	.	.	.	.	.	.	.	.	.	0.24	0.06	0	0	0.71
64	2000782	0	0	0	1	0	0	0	0	0.33	0.67	0	0.14	0.57	0.29	0	0.08	0.17	0.17	0.42	0.17	0	0	0.25	0.75	0
65	2000971	0.25	0.25	0	0	0.5	0	0	0	0	1	0	0	0.4	0.4	0.2	0	0	0.4	0.4	0.2	0.23	0	0.08	0.08	0.62
66	2001201	.	.	.	.	.	.	.	.	.	.	0	0	0.73	0.18	0.09	0	0	1	0	0	0	0	1	0	0
67	2001221	0	0	0	0	1	0	0.2	0.2	0	0.6	0	0	0	0	1	.	.	.	.	.	0.05	0.19	0	0	0.76
68	2001222	0	0	0	0	1	.	.	.	.	.	1	0	0	0	0	0	0	0	1	0	0.04	0	0	0.04	0.92
69	2001321	0	0	0.67	0	0.33	.	.	.	.	.	0.17	0	0.56	0.22	0.06	0	0	1	0	0	0	0	0.5	0.25	0.25
70	2001371	0.5	0.17	0	0.08	0.25	0.5	0	0	0	0.5	.	.	.	.	.	0.33	0	0	0.17	0.5	0.33	0	0	0.44	0.22
71	2001372	.	.	.	.	.	0	0.43	0.57	0	0	0	0.22	0.61	0.17	0	0	0.25	0.5	0.25	0	.	.	.	.	.
72	2001541	0.67	0	0.05	0.24	0.05	.	.	.	.	.	1	0	0	0	0	0.83	0	0	0.17	0	1	0	0	0	0
73	2001542	0.1	0	0	0.8	0.1	.	.	.	.	.	0	0	0	1	0	0.6	0	0.07	0.2	0.13	0	0	0	1	0
74	2001752	0	0.67	0	0	0.33	0.14	0	0	0	0.86	.	.	.	.	.	.	.	.	.	.	0.16	0.21	0	0	0.63
75	2002161	0	0	0	0.4	0.6	0	0	0	1	0	0	0	0.43	0.43	0.14	0.43	0	0.29	0	0.29	0.22	0.11	0.22	0.11	0.33
76	2002491	0	0	0	0	1	0	0	0	0	1	0	0	0.89	0	0.11	.	.	.	.	.	0.2	0.07	0	0	0.73
77	2002512	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	.	.	.	.	.	0.08	0.04	0.04	0	0.84
78	2002772	0	0	1	0	0	.	.	.	.	.	0	0	0.3	0.6	0.1	0.25	0	0.38	0.25	0.13	0	0	0.5	0.5	0
79	2003331	0.7	0	0.1	0.2	0	.	.	.	.	.	0	0	0.5	0.5	0	0.5	0	0	0.5	0	.	.	.	.	.
80	2003351	0	0	0.5	0	0.5	0	0	0	0	1	0	0.25	0.5	0	0.25	0	0	0.5	0.5	0	0.13	0	0.07	0.07	0.73
81	2003391	0	0	0	0	1	0	0.5	0.5	0	0	0.07	0	0.8	0.07	0.07	0	0	0.33	0.33	0.33	0.14	0.14	0.14	0.29	0.29
82	2003392	0	0	0	0.25	0.75	0	0	0	0	1	0	0	0.4	0	0.6	0	0	0.67	0.33	0	0.25	0.06	0.06	0.13	0.5
83	2003511	0	0	0	0	1	0.33	0.33	0	0	0.33	0	0	0	0	1	.	.	.	.	.	0.04	0.09	0.04	0	0.83
84	2003512	0	0	0	0	1	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	0.05	0.1	0	0	0.86
85	2003513	0	0	0	0	1	0.12	0.71	0	0.06	0.12	0	1	0	0	0	0	1	0	0	0	0.2	0.6	0.2	0	0
86	2003541	.	.	.	.	.	0	0.33	0.33	0	0.33	0	0	0.4	0.2	0.4	0	0.67	0	0	0.33	0	0	0.13	0.13	0.75
87	2010141	0	0	0	0	1	0.17	0.17	0.17	0	0.5	0	0	0	1	0	0	0.5	0	0.5	0	0.13	0.19	0	0.06	0.63
88	2010142	0	0	0	0	1	0	0	0	0.33	0.67	0	1	0	0	0	0	0	0.33	0	0.67	0.11	0.11	0	0.11	0.68
89	2010161	0	0	0	0.33	0.67	.	.	.	.	.	.	.	.	.	.	0	0	0	0	1	0.13	0	0	0	0.88
90	2010162	0.5	0.06	0	0.28	0.17	1	0	0	0	0	.	.	.	.	.	0.86	0	0	0.14	0	0.5	0	0	0.5	0
91	2010261	.	.	.	.	.	0	0.5	0	0	0.5	.	.	.	.	.	.	.	.	.	.	0	0.25	0	0	0.75
92	2010262	0.84	0	0	0	0.16	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.75	0	0	0	0.25
93	2010501	.	.	.	.	.	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	0	0.22	0	0	0.78

TABLE C1. Individual-Based Transition Matrix: Workers(4)

		Transition Matrix																								
No	Individual ID	AA	AB	AC	AD	AE	BA	BB	BC	BD	BE	CA	CB	CC	CD	CE	DA	DB	DC	DD	DD	EA	EB	EC	ED	EE
94	2010732	0.20	0	0.20	0.20	0.40	0	0.5	0	0	0.5	0.25	0	0	0.5	0.25	0	0	0.75	0.25	0	0.21	0.07	0	0	0.71
95	2011222	0.53	0.13	0.07	0.20	0.07	0.5	0	0	0.5	0	0.5	0	0	0.5	0	0.33	0	0.17	0.33	0.17	1	0	0	0	0
96	2011722	0.20	0.20	0.00	0	0.60	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	0.29	0.24	0	0	0.47
97	2011871	.	.	.	.	.	.	.	.	.	.	0	0	1	0	0	.	.	.	.	.	.	.	.	.	.
98	2011872	.	.	.	.	.	.	.	.	.	.	0	0	0.77	0.23	0	0	0	0.8	0.2	0	.	.	.	.	.
99	2012361	0.83	0	0	0	0.17	0	0	0	1	0	0	0	0.4	0.4	0.2	0	0	0.38	0.63	0	0.13	0.13	0	0.13	0.63
100	2012362	0.25	0	0	0	0.75	.	.	.	.	.	0.5	0	0	0	0.5	.	.	.	.	.	0.2	0	0.13	0	0.67
101	2012401	0.00	0	1	0	0.00	0	0.69	0	0	0.31	0	0	0	0	1	1	0	0	0	0	0	0.27	0.09	0.09	0.55
102	2012402	0.25	0	0	0	0.75	0.2	0.2	0	0	0.6	.	.	.	.	.	1	0	0	0	0	0.13	0.27	0	0.07	0.53
103	2012491	0.38	0	0	0	0.63	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	0.29	0	0	0	0.71
104	2012492	0.33	0.07	0	0.07	0.53	1	0	0	0	0	.	.	.	.	.	0	0	0	0	1	0.75	0	0	0	0.25
105	2012991	.	.	.	.	.	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	0	0.08	0	0	0.92
106	2012992	0	0	0.14	0.29	0.57	.	.	.	.	.	0.5	0	0.38	0.13	0	0	0	0.75	0.25	0	0.22	0	0.22	0	0.56
107	2013341	0	0	0	0	1.00	0	0	0	0	1	.	.	.	.	.	.	.	.	.	.	0.04	0.13	0	0	0.83
108	2013471	0.38	0	0.13	0	0.50	.	.	.	.	.	0	0	0	0	1	0	1	0	0	0	0.28	0	0	0.06	0.67
109	2013472	0.50	0.29	0	0.07	0.14	0.75	0	0	0	0.25	.	.	.	.	.	0.5	0	0	0.5	0	0.5	0	0	0.25	0.25

TABLE C2. Individual-Based Transition Matrix: Non-Workers (1)

		Transition Matrix																								
No	Individual ID	AA	AB	AC	AD	AE	BA	BB	BC	BD	BE	CA	CB	CC	CD	CE	DA	DB	DC	DD	DD	EA	EB	EC	ED	EE
1	1000031	0.57	0	0	0.43	0	.	.	.	.	.	0	0	0.2	0.8	0	0.1	0	0.3	0.6	0	.	.	.	.	.
2	1000032	0	0	1	0	0	.	.	.	.	.	0	0	0.9	0.1	0	0	0	0.3	0.7	0	.	.	.	.	.
3	1000551	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
4	1000552	.	.	.	.	.	.	.	.	.	.	0	0	1	0	0	.	.	.	.	.	.	.	.	.	.
5	1001071	.	.	.	.	.	.	.	.	.	.	0	0	0.8	0.2	0	0	0	0.8	0.2	0	.	.	.	.	.
6	1001072	.	.	.	.	.	.	.	.	.	.	0	0	0.6	0.4	0	0	0	0.5	0.5	0	.	.	.	.	.
7	1001161	.	.	.	.	.	.	.	.	.	.	0	0	0.8	0.2	0	0	0	0.6	0.4	0	.	.	.	.	.
8	1001251	0	0	0	0.83	0.17	.	.	.	.	.	0.2	0	0.2	0.7	0	0.3	0	0.3	0.5	0	1	0	0	0	0
9	1001441	.	.	.	.	.	.	.	.	.	.	0	0	0.5	0.5	0	0	0	0.8	0.3	0	.	.	.	.	.
10	1001451	.	.	.	.	.	.	.	.	.	.	0	0	1	0	0	.	.	.	.	.	.	.	.	.	.
11	1001471	.	.	.	.	.	.	.	.	.	.	0	0	0.7	0.3	0	0	0	0.6	0.4	0	.	.	.	.	.
12	1001591	.	.	.	.	.	.	.	.	.	.	0	0	0.4	0.6	0	0	0	0.5	0.5	0	.	.	.	.	.
13	1001721	.	.	.	.	.	.	.	.	.	.	0	0	0.6	0.4	0	0	0	0.8	0.2	0	.	.	.	.	.
14	1001722	0	0	1	0	0	.	.	.	.	.	0.1	0	0.8	0.1	0	0	0	1	0	0	.	.	.	.	.
15	1001951	.	.	.	.	.	.	.	.	.	.	0	0	0.6	0.4	0	0	0	0.4	0.6	0	.	.	.	.	.
16	1002881	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	0.5	0.5	0	.	.	.	.	.
17	1002882	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
18	1003181	0.29	0	0.14	0.57	0	.	.	.	.	.	1	0	0	0	0	0.3	0	0	0.6	0.1	0	0	0	1	0
19	1003241	.	.	.	.	.	.	.	.	.	.	0	0	0.7	0.3	0.1	0	0	0.7	0.3	0	0	0	0	1	0
20	1003341	0	0	0	1	0	.	.	.	.	.	0.1	0	0.5	0.4	0.1	0	0	0.8	0.3	0	0	0	0	1	0
21	1003342	0	0	0	1	0	.	.	.	.	.	0.1	0	0.5	0.3	0.2	0	0	0.6	0.3	0.1	0	0	0.5	0.5	0
22	1003491	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
23	1003492	.	.	.	.	.	.	.	.	.	.	0	0	0.8	0.2	0	0	0	0.5	0.5	0	.	.	.	.	.
24	1003502	0.38	0	0.38	0.25	0	.	.	.	.	.	0.4	0	0.3	0.3	0	0.1	0	0.7	0.1	0	.	.	.	.	.
25	1003511	.	.	.	.	.	.	.	.	.	.	0	0	0.7	0.3	0	0	0.1	0.6	0.3	0	.	.	.	.	.
26	1003512	.	.	.	.	.	.	.	.	.	.	0	0	0.6	0.4	0	0	0.1	0.4	0.4	0	.	.	.	.	.
27	1010101	.	.	.	.	.	.	.	.	.	.	0	0	0.7	0.3	0	0	0	1	0	0	.	.	.	.	.
28	1010102	.	.	.	.	.	.	.	.	.	.	0	0	0.8	0.2	0	0	0	0.8	0.2	0	.	.	.	.	.
29	1010332	0	0	1	0	0	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
30	1011001	0.5	0	0.5	0	0	.	.	.	.	.	0	0	0.9	0.1	0	0.3	0	0.7	0	0	0	0	1	0	0

TABLE C2. Individual-Based Transition Matrix: Non-Workers (2)

No	Individual ID	Transition Matrix																								
		AA	AB	AC	AD	AE	BA	BB	BC	BD	BE	CA	CB	CC	CD	CE	DA	DB	DC	DD	DD	EA	EB	EC	ED	EE
31	1011722	0	0	0	1	0	.	.	.	.	.	0	0	0.4	0.6	0	0.1	0	0.4	0.4	0	.	.	.	.	.
32	1012201	0.2	0	0.6	0.2	0	1	0	0	0	0	0.3	0.1	0.3	0.3	0	0.2	0	0.7	0.2	0	.	.	.	.	.
33	1012621	.	.	.	.	.	.	.	.	.	.	0	0	0.8	0.2	0	0	0	0.8	0.3	0	.	.	.	.	.
34	1012622	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
35	1012691	0	0	1	0	0	.	.	.	.	.	0.1	0	0.8	0.2	0	0	0	1	0	0	.	.	.	.	.
36	1012971	0	0	0	1	0	.	.	.	.	.	0.1	0	0.5	0.5	0	0	0	0.8	0.2	0	.	.	.	.	.
37	1013231	0.4	0	0.2	0.2	0.2	.	.	.	.	.	0.5	0	0	0.3	0.3	0.4	0	0.2	0.2	0.1	0.3	0	0	0.8	0
38	1013271	.	.	.	.	.	.	.	.	.	.	0	0	1	0.1	0	0	0	1	0	0	.	.	.	.	.
39	1013272	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
40	2000062	.	.	.	.	.	.	.	.	.	.	0	0	0.8	0.2	0	0	0	1	0	0	.	.	.	.	.
41	2000182	0	0	1	0	0	.	.	.	.	.	0	0	0.8	0.1	0	0	0	1	0	0	.	.	.	.	.
42	2000222	.	.	.	.	.	.	.	.	.	.	0.1	0	0.9	0	0	.	.	.	.	.	.	.	.	.	.
43	2000282	0	0	0.4	0.4	0.2	.	.	.	.	.	0.2	0	0.5	0.3	0	0.2	0	0.4	0.4	0	.	.	.	.	.
44	2000583	0.8	0	0	0.2	0	.	.	.	.	.	0.1	0	0.7	0.2	0	0	0	0.8	0.3	0	.	.	.	.	.
45	2000611	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
46	2000613	1	0	0	0	0	.	.	.	.	.	0	0	0.5	0.3	0.2	0.2	0	0.4	0.4	0	0	0	1	0	0
47	2000881	0.5	0	0	0.5	0	.	.	.	.	.	0.1	0	0.9	0	0	.	.	.	.	.	.	.	.	.	.
48	2000972	0.57	0	0.29	0.14	0	.	.	.	.	.	0.3	0	0.5	0.2	0	0	0	0.5	0.5	0	.	.	.	.	.
49	2001101	0	0	0.67	0	0.33	.	.	.	.	.	0	0	0.5	0.5	0	0.4	0	0.6	0	0	.	.	.	.	.
50	2001431	0.67	0	0	0.22	0.11	0	0.33	0	0	0.67	.	.	.	.	.	0.3	0.3	0	0.5	0	0.1	0.1	0	0	0.8
51	2001591	.	.	.	.	.	.	.	.	.	.	0	0	0.8	0.2	0	0	0	1	0	0	.	.	.	.	.
52	2001592	.	.	.	.	.	.	.	.	.	.	0	0	1	0	0	.	.	.	.	.	.	.	.	.	.
53	2002162	0.33	0	0	0.67	0	.	.	.	.	.	0	0	0	0.7	0.3	0.2	0	0.2	0.6	0.1	0.5	0	0	0.5	0
54	2002511	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	0.3	0.5	0.2	0	0	1	0	0
55	2002601	.	.	.	.	.	.	.	.	.	.	0.1	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
56	2002602	.	.	.	.	.	.	.	.	.	.	0.1	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
57	2002951	.	.	.	.	.	.	.	.	.	.	0	0	1	0	0	.	.	.	.	.	.	.	.	.	.
58	2003321	0.13	0.13	0.13	0.38	0.25	0.5	0.25	0.25	0	0	0	0	0	0.5	0.5	0.3	0.1	0	0.4	0.3	0.4	0.1	0	0.1	0.3
59	2003322	0.5	0.07	0	0.21	0.21	0.5	0	0	0	0.5	.	.	.	.	.	0.5	0	0	0	0.5	0.5	0.1	0	0	0.5
60	2003352	0	0	0	1	0	.	.	.	.	.	0	0	0.3	0.4	0.3	0	0	0.7	0.3	0	0.1	0	0.1	0	0.7
61	2003393	0.47	0.07	0.07	0.27	0.13	1	0	0	0	0	1	0	0	0	0	0.4	0	0	0.4	0.3	0.8	0	0	0.3	0

TABLE C2. Individual-Based Transition Matrix: Non-Workers (3)

		Transition Matrix																								
No	Individual ID	AA	AB	AC	AD	AE	BA	BB	BC	BD	BE	CA	CB	CC	CD	CE	DA	DB	DC	DD	DD	EA	EB	EC	ED	EE
62	2010221	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
63	2010222	.	.	.	.	.	.	.	.	.	.	0	0	0.8	0.3	0	0	0	0.5	0.5	0	.	.	.	.	.
64	2010502	.	.	.	.	.	0	0	1	0	0	0	0.1	0.4	0.5	0	0	0	0.8	0.3	0	.	.	.	.	.
65	2011051	0.27	0	0.18	0.55	0	.	.	.	.	.	0.5	0	0.3	0.3	0	0.4	0	0.1	0.6	0	.	.	.	.	.
66	2011052	0	0	0.75	0.25	0	.	.	.	.	.	0.3	0	0.6	0.2	0	0.2	0	0.6	0.2	0	.	.	.	.	.
67	2011111	0.33	0	0	0.17	0.5	0	0	0	1	0	0.7	0	0	0.3	0	0.2	0.2	0.2	0.4	0	0.2	0	0.2	0.2	0.4
68	2011221	0.84	0.08	0	0	0.08	1	0	0	0	0	.	.	.	.	.	.	.	.	.	.	1	0	0	0	0
69	2011401	0	0	0	1	0	.	.	.	.	.	0.1	0	0.3	0.6	0	0.1	0	0.3	0.6	0	.	.	.	.	.
70	2011402	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	0	0	1	0	0	.	.	.	.	.
71	2011791	0	0	1	0	0	.	.	.	.	.	0	0	0.8	0.2	0	0	0	0.8	0.3	0	.	.	.	.	.
72	2011821	.	.	.	.	.	.	.	.	.	.	0	0	0.5	0.5	0	0	0	0.6	0.4	0	.	.	.	.	.
73	2011861	.	.	.	.	.	.	.	.	.	.	0	0	0.7	0.3	0	0	0	0.5	0.5	0	.	.	.	.	.
74	2011862	.	.	.	.	.	.	.	.	.	.	0	0	0.7	0.3	0	0	0	0.6	0.4	0	.	.	.	.	.
75	2011971	.	.	.	.	.	.	.	.	.	.	0	0	0.1	0.8	0.1	0	0	0.4	0.6	0.1	0	0	1	0	0
76	2012061	0.5	0.08	0.17	0.08	0.17	1	0	0	0	0	0.3	0	0.5	0.1	0.1	0.5	0	0.3	0	0.3	0.5	0	0.3	0.3	0
77	2012481	0.29	0	0.43	0	0.29	0	0	0	0	1	0.3	0.1	0.3	0.2	0.1	0.5	0	0	0	0.5	0	0	0.4	0.3	0.3
78	2012482	0	0	1	0	0	.	.	.	.	.	0.2	0	0.6	0.1	0.2	1	0	0	0	0	0	0	1	0	0
79	2012761	0	0.25	0.5	0.25	0	0	0	0	1	0	0.1	0	0.4	0.3	0.3	0.3	0	0.5	0	0.3	0.1	0	0.1	0	0.8
80	2012851	.	.	.	.	.	.	.	.	.	.	0	0	0.9	0.1	0	.	.	.	.	.	.	.	.	.	.
81	2012972	.	.	.	.	.	.	.	.	.	.	0	0	1	0	0	.	.	.	.	.	.	.	.	.	.
82	2013251	.	.	.	.	.	.	.	.	.	.	0	0	1	0	0	.	.	.	.	.	.	.	.	.	.
83	2013321	.	.	.	.	.	.	.	.	.	.	0	0	0.7	0.3	0	0	0	0.7	0.3	0	.	.	.	.	.
84	2013322	0	0	0	1	0	.	.	.	.	.	0.1	0	0.7	0.3	0	0.1	0	0.7	0.1	0	.	.	.	.	.
85	2013381	0.38	0	0.38	0.25	0	.	.	.	.	.	0.2	0	0.2	0.3	0.3	0.4	0	0.1	0.5	0.1	0	0	0.3	0.5	0.3
86	2013382	0	0	0.33	0.33	0.33	.	.	.	.	.	0.2	0	0.6	0.3	0	0.1	0	0.3	0.5	0.1	0	0	0.5	0.5	0

TABLE C3 Observed and Limiting Distribution of Representative Patterns: Workers (1)

No	Individual ID	A	B	C	D	E	p1	p2	p3	p4	p5
1	1000091	0.15	0.26	0.04	0.52	0.04	0.21	0	0.07	0.72	0
2	1000481	0.11	0.33	0	0	0.56	0.14	0.27	0.11	0	0.48
3	1000521	0.03	0.2	0.03	0.03	0.7	0.04	0.14	0.04	0.04	0.74
4	1000531	0.03	0.23	0.1	0	0.63	0.03	0.21	0.11	0	0.65
5	1000761	0.1	0.77	0	0	0.13	0.11	0.74	0	0	0.15
6	1000851	0.07	0.2	0.07	0	0.67	0.07	0.21	0.07	0	0.65
7	1000852	0.26	0.04	0.3	0.17	0.22	0.28	0.04	0.29	0.16	0.23
8	1001041	0.37	0.07	0	0	0.57	0.38	0.08	0	0	0.54
9	1001042	0.47	0.03	0.03	0	0.47	0.45	0.04	0.04	0	0.47
10	1001051	0.43	0.03	0	0	0.53	0.48	0.05	0	0	0.47
11	1001053	0.33	0.1	0	0.03	0.53	0.3	0.09	0	0.04	0.57
12	1001172	0.16	0.16	0.12	0.04	0.52	0.18	0.19	0.11	0.03	0.49
13	1001452	0.3	0.03	0	0	0.67	0.28	0.03	0	0	0.69
14	1001472	0.04	0.63	0.04	0.04	0.26	0.08	0.66	0.04	0	0.22
15	1001592	0.07	0.4	0	0	0.53	0.06	0.39	0	0	0.55
16	1001832	0.22	0.04	0.52	0.17	0.04	0.27	0	0.53	0.15	0.05
17	1001891	0.17	0.2	0.03	0.03	0.57	0.17	0.21	0.03	0.04	0.55
18	1001892	0.33	0.13	0.03	0	0.5	0.23	0.21	0.02	0	0.54
19	1001893	0.2	0.23	0	0	0.57	0.21	0.24	0	0	0.55
20	1001941	0.14	0.25	0	0	0.61	0.12	0.25	0	0	0.63
21	1001961	0.1	0.43	0	0.03	0.43	0.1	0.45	0	0.04	0.41
22	1002291	0.14	0.57	0	0	0.29	0.14	0.6	0	0	0.26
23	1002901	0.27	0.2	0.03	0	0.5	0.26	0.19	0.03	0	0.52
24	1002931	0.37	0.13	0	0.03	0.47	0.37	0.11	0	0.03	0.49
25	1003091	0.07	0.47	0.03	0	0.43	0.04	0.49	0.03	0	0.44
26	1003201	0.08	0.24	0	0	0.68	0.08	0.2	0	0	0.72
27	1003351	0.13	0.13	0.03	0.03	0.67	0.18	0.13	0.03	0.03	0.63
28	1003411	0.12	0.08	0.19	0.35	0.27	0.17	0.08	0.13	0.38	0.24
29	1003412	0.28	0.04	0.44	0.12	0.12	0.34	0.04	0.41	0.1	0.11
30	1003493	0.93	0.03	0	0.03	0	0.91	0	0	0	0.09
31	1003501	0.33	0.1	0.03	0.27	0.27	0.33	0.11	0.03	0.26	0.27
32	1003521	0.11	0.32	0	0	0.57	0.12	0.26	0	0	0.62
33	1010331	0.17	0.07	0.03	0	0.73	0.17	0.08	0.03	0	0.72
34	1010561	0.3	0.2	0.03	0.17	0.3	0.3	0.03	0	0.19	0.48
35	1011351	0.26	0.26	0.04	0	0.43	0.25	0.27	0.04	0	0.44
36	1012001	0.1	0.21	0	0.07	0.62	0.11	0.19	0	0.06	0.64
37	1012202	0.44	0.12	0.12	0.2	0.12	0.42	0.12	0.12	0.21	0.13
38	1012231	0.1	0.21	0	0.03	0.66	0.07	0.21	0	0.03	0.69
39	1012552	0.23	0	0	0.13	0.63	0.26	0	0	0.14	0.6
40	1012972	0.21	0.13	0.13	0	0.54	0.22	0.13	0.13	0	0.52
41	1013201	0.17	0.03	0.07	0.03	0.69	0.22	0.13	0.13	0	0.52
42	1013261	0.13	0.13	0.13	0.08	0.54	0.13	0.14	0.06	0.07	0.6
43	1013351	0.14	0.03	0.03	0.1	0.69	0.15	0.03	0.03	0.11	0.68
44	1013381	0.11	0.07	0.04	0	0.79	0.11	0.08	0.04	0	0.77
45	1013391	0.3	0.26	0.11	0.07	0.26	0.33	0.3	0.05	0.08	0.24
46	1013393	0.31	0.24	0.03	0	0.41	0.38	0.27	0.04	0	0.31

TABLE C3 Observed and Limiting Distribution of Representative Patterns: Workers (2)

No	Individual ID	A	B	C	D	E	p1	p2	p3	p4	p5
47	2000061	0.36	0	0.52	0.04	0.08	0.38	0	0.46	0.08	0.08
48	2000171	0.07	0.33	0.03	0	0.57	0.1	0.35	0.04	0	0.51
49	2000181	0.13	0.03	0	0	0.83	0.13	0.03	0	0	0.84
50	2000191	0.28	0.31	0.14	0.03	0.24	0.24	0.33	0.14	0.04	0.25
51	2000212	0.04	0.22	0	0.07	0.67	0.04	0.23	0	0.08	0.65
52	2000221	0.43	0	0.3	0.17	0.09	0.49	0	0.34	0.11	0.06
53	2000482	0.2	0.1	0	0	0.7	0.21	0.1	0	0	0.69
54	2000501	0.23	0	0.13	0.37	0.27	0.3	0	0.15	0.28	0.27
55	2000581	0.67	0.17	0.07	0.1	0	0.05	0.04	0	0	0.91
56	2000582	0.1	0.03	0	0	0.86	0.04	0	0	0	0.96
57	2000741	0.03	0	0	0	0.97	0.24	0.13	0	0	0.63
58	2000781	0	0	1	0	0	0.03	0.11	0.27	0.44	0.15
59	2000782	0.04	0.11	0.25	0.46	0.14	0.13	0.04	0.18	0.18	0.47
60	2000971	0.14	0.03	0.17	0.17	0.48	0.03	0.18	0.03	0	0.76
61	2001221	0.03	0.17	0.03	0	0.76	0.04	0.18	0.04	0	0.74
62	2001321	0.1	0	0.6	0.17	0.13	0.52	0.04	0	0.04	0.4
63	2001371	0.4	0.07	0	0.23	0.3	0.37	0.07	0	0.22	0.34
64	2001541	0.73	0	0.03	0.2	0.03	0.69	0	0.07	0.17	0.07
65	2001542	0.33	0	0.03	0.53	0.1	0.34	0	0.04	0.52	0.1
66	2001752	0.13	0.23	0	0	0.63	0.13	0.23	0	0	0.64
67	2002161	0.17	0.03	0.23	0.23	0.33	0.18	0.03	0.24	0.24	0.31
68	2002491	0.1	0.03	0.31	0	0.55	0.16	0.06	0	0	0.78
69	2002512	0.07	0.03	0.03	0	0.86	0.07	0.03	0.03	0	0.87
70	2002772	0.09	0	0.43	0.39	0.09	0.09	0	0.42	0.4	0.09
71	2003331	0.59	0	0.12	0.29	0	0.56	0	0.11	0.33	0
72	2003351	0.08	0.04	0.2	0.08	0.6	0.07	0.06	0.23	0.08	0.56
73	2003391	0.07	0.07	0.5	0.13	0.23	0.06	0.06	0.53	0.14	0.21
74	2003392	0.13	0.03	0.17	0.13	0.53	0.12	0.03	0.21	0.14	0.5
75	2003511	0.07	0.1	0.03	0	0.8	0.07	0.11	0.03	0	0.79
76	2003512	0.04	0.08	0	0	0.88	0.04	0.09	0	0	0.87
77	2003513	0.11	0.64	0.04	0.04	0.18	0.1	0.65	0.04	0.04	0.17
78	2010141	0	0.11	0.18	0.11	0.61	0.1	0.2	0.03	0.13	0.54
79	2010142	0.1	0.21	0.03	0.1	0.55	0.07	0.11	0.03	0.1	0.69
80	2010162	0.07	0.11	0.04	0.11	0.68	0.1	0	0	0.03	0.87
81	2010261	0.1	0	0	0.03	0.86	0.61	0.04	0	0.25	0.1
82	2010262	0.62	0.03	0	0.24	0.1	0.82	0	0	0	0.18
83	2010732	0.17	0.07	0.13	0.17	0.47	0.18	0.07	0.14	0.14	0.47
84	2011222	0.43	0.07	0.07	0.25	0.18	0.52	0.06	0.08	0.26	0.08
85	2011722	0.21	0.21	0	0	0.59	0.22	0.19	0	0	0.59
86	2012361	0.21	0.03	0.17	0.31	0.28	0.15	0.03	0.24	0.38	0.2
87	2012362	0.23	0	0.09	0	0.68	0.24	0	0.09	0	0.67
88	2012401	0.04	0.5	0.07	0	0.39	0.09	0.37	0.09	0.03	0.42
89	2012402	0.19	0.19	0	0.04	0.58	0.2	0.19	0	0.04	0.57
90	2012491	0.3	0	0	0	0.7	0.32	0	0	0	0.68
91	2012492	0.53	0.03	0	0.03	0.4	0.52	0.04	0	0.04	0.4
92	2012992	0.24	0	0.31	0.14	0.31	0.23	0	0.33	0.14	0.3
93	2013341	0.03	0.13	0	0	0.83	0.04	0.11	0	0	0.85
94	2013471	0.28	0.03	0.03	0.03	0.62	0.03	0.11	0	0	0.86

TABLE C3 Observed and Limiting Distribution of Representative Patterns: Workers (2)

No	Individual ID	A	B	C	D	E	p1	p2	p3	p4	p5
95	2013472	0.56	0.16	0	0.12	0.16	0.55	0.16	0	0.17	0.12
97	1001541	0	0.22	0	0.04	0.74	0	0.21	0	0.05	0.74
98	1011721	0	0.55	0	0.07	0.38	0	0.55	0	0.07	0.38
99	2000281	0	0.57	0	0.03	0.4	0	0.53	0	0.03	0.44
100	2001201	0	0	0.8	0.13	0.07	0	0	0.79	0.14	0.07
101	2001222	0.07	0	0.03	0.07	0.83	0.04	0	0.18	0.04	0.74
102	2001372	0	0.27	0.6	0.13	0	0	0.28	0.59	0.13	0
103	2003541	0.73	0	0.03	0.2	0.03	0	0.11	0.19	0.11	0.59
104	2010261	0	0.32	0	0	0.68	0	0.33	0	0	0.67
105	2010501	0	0.18	0	0	0.82	0	0.18	0	0	0.82
106	2011872	0	0	0.79	0.21	0	0	0	0.78	0.22	0
107	2012991	0	0.07	0	0	0.93	0	0.07	0	0	0.93

TABLE C4 Observed and Limiting Distribution of Representative Patterns: Non-Workers (1)

No	Individual ID	A	B	C	D	E	p1	p2	p3	p4	p5
1	1000032	0.03	0	0.83	0.14	0	0	0	0.75	0.25	0
2	1001251	0.2	0	0.2	0.57	0.03	0.24	0	0.19	0.52	0.05
3	1001722	0.07	0	0.83	0.1	0	0.08	0	0.83	0.09	0
4	1003181	0.32	0	0.05	0.58	0.05	0.3	0	0.03	0.61	0.06
5	1003341	0	0	0.6	0.36	0.04	0.05	0	0.52	0.38	0.05
6	1003342	0.04	0	0.52	0.32	0.12	0.05	0	0.51	0.35	0.09
7	1003502	0.32	0	0.43	0.25	0	0.3	0	0.45	0.25	0
8	1010332	0.04	0	0.96	0	0	0	0	0.91	0.09	0
9	1011001	0.07	0	0.8	0.1	0.03	0.05	0	0.86	0.09	0
10	1011722	0.07	0	0.37	0.56	0	0.11	0	0.36	0.53	0
11	1012201	0.24	0.04	0.48	0.24	0	0.28	0.05	0.46	0.21	0
12	1012691	0.04	0	0.83	0.13	0	0.08	0	0.83	0.09	0
13	1012971	0.04	0	0.58	0.38	0	0.06	0	0.58	0.36	0
14	1013231	0.39	0	0.14	0.32	0.14	0.4	0	0.14	0.3	0.16
15	2000182	0.03	0	0.87	0.1	0	0	0	0.83	0.17	0
16	2000282	0.18	0	0.43	0.39	0	0.19	0	0.43	0.34	0.04
17	2000583	0.22	0	0.56	0.22	0	0.27	0	0.53	0.2	0
18	2000972	0.29	0	0.46	0.25	0	0.33	0	0.43	0.24	0
19	2001101	0.12	0	0.58	0.27	0.03	0.15	0	0.53	0.27	0.05
20	2001431	0.31	0.1	0	0.14	0.45	0.25	0.12	0	0.1	0.53
21	2003321	0.27	0.13	0.07	0.27	0.26	0.28	0.12	0.05	0.24	0.31
22	2003322	0.47	0.07	0	0.1	0.36	0.5	0.08	0	0.1	0.32
23	2003352	0.04	0	0.36	0.3	0.3	0.07	0	0.33	0.28	0.32
24	2003393	0.5	0.03	0.03	0.27	0.17	0.54	0.05	0.05	0.29	0.07
25	2011051	0.37	0	0.13	0.5	0	0.35	0	0.17	0.48	0
26	2011052	0.19	0	0.62	0.19	0	0.22	0	0.64	0.14	0
27	2011111	0.29	0.05	0.14	0.29	0.23	0.27	0.07	0.11	0.33	0.22
28	2011221	0.87	0.07	0	0	0.06	0.83	0.08	0	0	0.09
29	2011401	0.07	0	0.3	0.63	0	0.1	0	0.27	0.63	0
30	2011791	0.03	0	0.8	0.17	0	0	0	0.8	0.2	0
31	2012061	0.43	0.03	0.27	0.2	0.07	0.46	0.05	0.3	0.09	0.1
32	2012481	0.23	0.03	0.33	0.13	0.28	0.23	0.03	0.3	0.15	0.29
33	2012482	0.1	0	0.76	0.04	0.1	0.07	0	0.65	0.28	0
34	2012761	0.14	0.04	0.29	0.14	0.39	0.11	0.03	0.28	0.14	0.44
35	2013322	0.07	0	0.63	0.3	0	0.09	0	0.64	0.27	0
36	2013381	0.3	0	0.2	0.37	0.13	0.32	0	0.24	0.36	0.08
37	2013382	0.11	0	0.41	0.41	0.07	0.12	0	0.45	0.34	0.09
38	1000551	0	0	0.89	0.11	0	0	0	0.75	0.25	0
39	1001071	0	0	0.81	0.19	0	0	0	0.8	0.2	0
40	1001072	0	0	0.58	0.42	0	0	0	0.56	0.44	0
41	1001161	0	0	0.76	0.24	0	0	0	0.75	0.25	0
42	1001441	0	0	0.61	0.39	0	0	0	0.62	0.38	0
43	1001471	0	0	0.65	0.35	0	0	0	0.67	0.33	0
44	1001591	0	0	0.45	0.55	0	0	0	0.45	0.55	0
45	1001721	0	0	0.67	0.33	0	0	0	0.67	0.33	0
46	1001951	0	0	0.44	0.56	0	0	0	0.5	0.5	0

TABLE C4 Observed and Limiting Distribution of Representative Patterns: Non-Workers (2)

No	Individual ID	A	B	C	D	E	p1	p2	p3	p4	p5
47	1002881	0	0	0.83	0.17	0	0	0	0.83	0.17	0
48	1002882	0	0	0.9	0.1	0	0	0	0.91	0.09	0
49	1003241	0	0	0.65	0.3	0.05	0	0.65	0.28	0.07	0
50	1003491	0	0	0.89	0.11	0	0	0	0.91	0.09	0
51	1003492	0	0	0.76	0.24	0	0	0	0.71	0.29	0
52	1003511	0	0.04	0.63	0.33	0	0	0	0.67	0.33	0
53	1003512	0	0.05	0.52	0.43	0	0	0	0.56	0.44	0
54	1010101	0	0	0.78	0.22	0	0	0	0.77	0.23	0
55	1010102	0	0	0.78	0.22	0	0	0	0.8	0.2	0
56	1012621	0	0	0.8	0.2	0	0	0	0.8	0.2	0
57	1012622	0	0	0.92	0.08	0	0	0	0.91	0.09	0
58	1013271	0	0	0.96	0.04	0	0	0	0.53	0.47	0
59	1013272	0	0	0.94	0.06	0	0	0	0.53	0.47	0
60	2000062	0	0	0.82	0.18	0	0	0	0.83	0.17	0
61	2000613	0.13	0	0.4	0.4	0.07	0	0	0.91	0.09	0
62	2000881	0.15	0	0.77	0.08	0	0	0	0.13	0.87	0
63	2002601	0.04	0	0.92	0.04	0	0	0	0.9	0.1	0
64	2002602	0.06	0	0.88	0.06	0	0	0	0.9	0.1	0
65	2010221	0	0	0.94	0.06	0	0	0	0.9	0.1	0
66	2010222	0	0	0.73	0.27	0	0	0	0.71	0.29	0
67	2010502	0	0.03	0.55	0.42	0	0	0	0.62	0.38	0
68	2011402	0	0	0.9	0.1	0	0	0	0	1	0
69	2011821	0	0	0.5	0.5	0	0	0	0.55	0.45	0
70	2011861	0	0	0.57	0.43	0	0	0	0.63	0.37	0
71	2011862	0	0	0.41	0.59	0	0	0	0.67	0.33	0
72	2011971	0	0	0.3	0.63	0.07	0	0	0.35	0.56	0.09
73	2013321	0	0	0.63	0.37	0	0	0	0.7	0.3	0